INTERNATIONAL JOURNAL OF INFORMATION AND COMMUNICATION TECHNOLOGY TRENDS

Vol. 6 No. 02 (2026)

e.ISSN: 2409-5222

https://ijictt.ictt.info

Alias-Controlled Spectral Sparsification for Million-Token Sequence Models

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Abstract

The rapid evolution of large language models has driven the demand for massively extended context windows, culminating in the pursuit of million-token sequence modeling capabilities. However, scaling the self-attention mechanism to such unprecedented lengths introduces prohibitive computational and memory bottlenecks due to its inherent quadratic complexity. While various sparsification and low-rank approximation techniques have been proposed, they frequently suffer from severe information loss and structural degradation when applied to extremely long sequences. This paper introduces a novel framework termed Alias-Controlled Spectral Sparsification, which leverages principles from graph signal processing to selectively prune attention graphs in the spectral domain. By rigorously analyzing the aliasing artifacts that emerge during aggressive token downsampling, we develop a specialized anti-aliasing filter that preserves the fundamental low-frequency semantic structures while systematically attenuating high-frequency noise. Our methodology enables the compression of million-token sequences into highly tractable spectral representations without sacrificing critical contextual dependencies. Extensive theoretical analysis and empirical evaluations on long-document benchmarks demonstrate that our approach significantly outperforms existing sparse attention mechanisms in both perplexity retention and hardware efficiency. The proposed architecture achieves near-linear time complexity, offering a scalable and robust solution for next-generation sequence models processing ultra-long contexts.

Keywords: *Sequence Modeling, Spectral Sparsification, Self-Attention, Graph Signal Processing, Anti-Aliasing*

1. Introduction

The paradigm of natural language processing has been fundamentally transformed by the advent of transformer architectures, which rely heavily on the self-attention mechanism to capture complex dependencies across discrete tokens. As these sequence models have grown in parameter count and capability, a primary frontier of ongoing research has been the expansion of the context window. Early models were constrained to sequence lengths of a few hundred tokens, fundamentally limiting their utility in tasks requiring holistic document understanding, long-term multi-turn conversations, and repository-level code generation. Recent advancements have pushed this boundary significantly, yet the aspiration to

seamlessly process million-token sequences introduces severe theoretical and practical challenges. The core of this challenge lies in the quadratic scaling of standard self-attention, where the computation of the attention matrix demands resources proportional to the square of the sequence length. This limitation forms the primary motivation for the research presented in this manuscript [1, 2]. Addressing the quadratic bottleneck has catalyzed a vast body of literature focused on efficient attention mechanisms. Spatial sparsification techniques attempt to limit the receptive field of each token to a local neighborhood or a set of predefined sparse patterns. While effective for moderate lengths, these approaches often fail to capture the global, long-range dependencies crucial for understanding million-token contexts. Alternatively, low-rank approximations hypothesize that the attention matrix manifests intrinsic low-rank properties, allowing for decomposition into smaller matrices. However, empirical evidence suggests that as sequences scale into the millions of tokens, the attention matrix becomes increasingly full-rank in localized regions, causing low-rank methods to suffer from unacceptable precision loss and contextual hallucination [3]. Furthermore, hardware-aware optimizations provide constant-factor speedups but do not alter the asymptotic complexity, eventually hitting physical hardware limits when sequence lengths reach extreme scales [4, 5]. To overcome these fundamental limitations, researchers have recently turned to the domain of graph signal processing to reconceptualize the attention mechanism. By modeling the token sequence as a fully connected graph where edge weights correspond to attention scores, it becomes possible to analyze sequence dependencies in the spectral domain. Spectral sparsification aims to reduce the graph's complexity by preserving its principal spectral properties, primarily through the retention of dominant eigenvalues and eigenvectors. However, a critical yet historically overlooked issue in spectral downsampling of discrete token graphs is the phenomenon of aliasing. When a highly dense sequence graph is aggressively subsampled to meet computational constraints, high-frequency spectral components incorrectly fold into the low-frequency bands. This spectral folding, or aliasing, corrupts the core semantic representation of the sequence, leading to catastrophic degradation in model performance and catastrophic forgetting of distant context [6]. This paper proposes a comprehensive solution to this problem through the introduction of Alias-Controlled Spectral Sparsification. We systematically investigate the mathematical mechanisms of spectral aliasing in transformer attention graphs and design a novel anti-aliasing filter tailored for discrete sequence models. By applying this filter prior to the sparsification step, we ensure that high-frequency noise is properly attenuated, thereby protecting the integrity of the essential low-frequency semantic signals during aggressive downsampling [7, 8]. Our approach bridges the theoretical rigor of classical signal processing with the highly empirical domain of large language model architecture. The subsequent sections of this paper are organized to provide a deep, exhaustive exploration of the proposed methodology. Section 2 establishes a thorough background on sequence modeling and graph signal processing, delineating the related work that forms the foundation of our research. Section 3 formalizes the theoretical underpinnings of spectral sparsification in the context of attention matrices. Section 4 details the core mathematical formulation of the alias-controlled sparsification technique, including the design and optimization of the anti-aliasing filter. Section 5 describes the system architecture and hardware implementation strategies required to deploy this technique efficiently on modern parallel compute architectures. Section 6 presents extensive experimental results, analyzing the performance of our method across various long-context benchmarks. Finally, Section 7 concludes the paper and discusses promising avenues for future research in the realm of ultra-long sequence modeling.

2. Background and Related Work

2.1 Evolution of Long-Context Sequence Models

The historical progression of sequence modeling has been characterized by a continuous struggle against the limitations of memory and computational complexity. Recurrent neural networks and their variants, such as long short-term memory networks, initially dominated the field by processing tokens sequentially. While this approach required only linear memory with respect to the sequence length, it inherently bottlenecked parallel computation and suffered from vanishing gradients over long distances, making it unsuitable for sequences exceeding a few thousand tokens [9, 10]. The introduction of the transformer

architecture revolutionized sequence processing by abandoning recurrence in favor of global self-attention, enabling massive parallelization and direct modeling of dependencies regardless of distance [11].

However, the global attention mechanism fundamentally requires the computation of pairwise similarities between all tokens in the sequence. For a sequence of length N, this necessitates the materialization of an N by N attention matrix, leading to quadratic time and space complexity. As the research community sought to apply transformers to entire books, extensive legal documents, and large codebases, this quadratic scaling rapidly became the primary structural barrier in artificial intelligence research [12, 13]. Consequently, the development of efficient transformers has become a distinct and highly active subfield, categorized broadly into sparse attention, linear attention, and memory-augmented networks.

2.2 Efficient Attention Mechanisms

Sparse attention mechanisms aim to reduce complexity by constraining the attention matrix to a sparse topology. Early approaches utilized fixed patterns, such as sliding windows and dilated strided windows, to reduce the complexity to linear or log-linear scales. Models employing these techniques demonstrated significant speedups but often failed on tasks requiring complex, multi-hop reasoning over long distances, as the fixed sparsity patterns could not dynamically adapt to the linguistic structure of the input [14]. To address this, learnable and dynamic sparsity patterns were introduced, utilizing routing networks or locality-sensitive hashing to select the most relevant tokens for attention dynamically. While theoretically appealing, these methods frequently introduce substantial overhead in the routing mechanism itself, sometimes negating the computational benefits of sparsity when deployed on highly optimized matrix multiplication hardware [15, 16]. Linear attention approaches, conversely, seek to bypass the softmax operation that necessitates the materialization of the full attention matrix. By utilizing kernel feature maps to approximate the softmax function, these models can leverage the associative property of matrix multiplication to compute attention in linear time [17, 18]. Despite their elegant theoretical formulation, kernel-based linear transformers often struggle with training instability and fail to match the empirical performance of standard softmax attention, particularly in retaining sharp, highly focused attention scores that are critical for tasks like exact string matching and associative recall within million-token contexts [19].

2.3 Graph Signal Processing in Sequence Models

A more recent and highly promising trajectory in sequence modeling involves the application of graph signal processing. In this paradigm, the sequence of tokens is viewed as a signal defined on the vertices of a graph, where the edges represent the syntactic and semantic relationships inferred by the attention mechanism. Graph signal processing provides a rigorous mathematical framework for analyzing the spectral properties of these token graphs, translating concepts such as frequency, filtering, and sampling from the continuous time domain into the discrete graph domain [20, 21]. In the context of self-attention, the attention matrix can be interpreted as a transition matrix of a random walk on the token graph, or equivalently, as a shift operator in the graph spectral domain. Eigen-decomposition of this operator reveals a spectrum where low-frequency eigenvectors correspond to smooth, slowly varying contextual themes across the document, while high-frequency eigenvectors capture localized, highly specific token interactions [22]. Previous studies have leveraged this spectral perspective to prune the attention graph by projecting the token representations onto the subspace spanned by the dominant low-frequency eigenvectors, achieving significant dimensionality reduction.

2.4 The Aliasing Problem in Spectral Downsampling

Despite the success of spectral dimensionality reduction, a critical vulnerability emerges when these techniques are scaled to million-token sequences. When a sequence graph is aggressively downsampled to a computationally tractable size, the Nyquist-Shannon sampling theorem equivalent for graphs dictates that high-frequency signals cannot be accurately represented in the reduced subspace [23, 24]. If these high-frequency components are not explicitly removed prior to sampling, they fold into the low-frequency spectrum. This phenomenon, known as aliasing, heavily distorts the dominant eigenvectors. In language models, aliasing manifests as contextual hallucination, where the model falsely conflates distinct topics from distant parts of the document due to the spectral interference. The failure of existing spectral

transformers to account for and mitigate aliasing constitutes the primary research gap that this paper addresses.

3. Theoretical Foundations of Spectral Sparsification

3.1 Spectral Graph Theory in Attention Matrices

To rigorously formulate the alias-controlled spectral sparsification, it is necessary to first establish the mathematical foundation of spectral graph theory as it applies to transformer attention matrices. Let the input to a self-attention layer be a sequence of N tokens, represented by a feature matrix where each row corresponds to a token embedding of dimension d. The standard self-attention mechanism computes the queries, keys, and values through linear projections. The unnormalized attention scores are obtained by the dot product of queries and keys, and the application of the softmax function yields the stochastic attention matrix, which we denote as the adjacency matrix of a directed, weighted graph [25, 26]. For the purpose of spectral analysis, we symmetrize this matrix to construct an undirected graph representation, which guarantees real eigenvalues and a complete set of orthogonal eigenvectors. We define the normalized graph Laplacian, a fundamental operator in spectral graph theory that describes the flow of information across the token graph. The normalized Laplacian encapsulates the geometric and structural properties of the sequence dependencies. The eigendecomposition of this Laplacian forms the basis of the graph Fourier transform [27].

$$L = I - D^{-\frac{1}{2}}AD^{-\frac{1}{2}} = ULambdaU^{top}$$

In this block mathematical formulation, the identity matrix is adjusted by the degree matrix and the adjacency matrix to yield the Laplacian. The decomposition produces the eigenvector matrix and the diagonal matrix of eigenvalues. The eigenvalues represent the graph frequencies, ordered from smallest to largest. The lowest frequencies correspond to the most significant, structurally dense clusters within the document, often mapping to broad topical segments or continuous narrative arcs. Conversely, the highest frequencies correspond to isolated, idiosyncratic token relationships, such as rare named entities or punctuation patterns [28, 29].

3.2 Subspace Projection and Information Retention

Spectral sparsification fundamentally operates by projecting the high-dimensional token graph onto a lower-dimensional subspace spanned by a subset of these eigenvectors. By selecting only the first k eigenvectors corresponding to the smallest eigenvalues, we construct a projection operator that acts as an ideal low-pass filter in the graph spectral domain. The assumption inherent in this approach is that the primary semantic information of the million-token sequence is bandlimited, meaning it can be adequately reconstructed from the low-frequency components alone [30]. However, exact eigendecomposition of an N by N matrix requires cubic time complexity, which is vastly more prohibitive than the quadratic complexity of standard attention. Therefore, practical spectral sparsification relies on fast approximation algorithms, such as the Lanczos method or randomized singular value decomposition, to estimate the dominant eigenspace without fully materializing the Laplacian. Even with these approximations, the direct projection method is highly susceptible to the aliasing artifacts described in the previous section when the downsampling ratio is extreme, necessitating the integration of a dedicated anti-aliasing mechanism [31, 32].

4. Alias-Controlled Sparsification Methodology

4.1 Anti-Aliasing Filter Design

The core innovation of our methodology is the introduction of an alias-controlled objective within the spectral sparsification pipeline. Before the sequence graph is subsampled, we apply a specially designed graph filter to strictly bandlimit the token signals, forcing the high-frequency energy to zero and thereby preventing it from folding into the target low-frequency subspace. Designing an effective anti-aliasing filter for discrete token graphs is challenging because the graph topology is not fixed; it is dynamically generated by the attention mechanism and varies continuously during training and inference [33, 34].

We propose a polynomial graph filter, which can be applied directly to the token features without requiring the explicit computation of the eigenvectors. By expressing the filter as a Chebyshev polynomial of the Laplacian, we achieve a highly localized, distributed operation that scales linearly with the number of non-zero edges in the approximated attention graph. The coefficients of this polynomial are optimized to approximate a step function in the spectral domain, featuring a flat passband for the low frequencies and a steep roll-off into the stopband for the high frequencies.

Table 1Theoretical Complexity Comparison

Model Architecture	Time Complexity	Memory Complexity	Aliasing Mitigation
Standard Transformer	Quadratic	Quadratic	Not Applicable
Low-Rank Attention	Linear-Logarithmic	Linear	None
Standard Spectral	Linear-Logarithmic	Linear	None
Alias-Controlled (Ours)	Linear-Logarithmic	Linear	Explicit Filter

The table above illustrates the theoretical complexity advantages of our approach. While maintaining the favorable linear-logarithmic time and linear memory complexities of standard spectral methods, our architecture uniquely incorporates explicit aliasing mitigation, adding only a marginal constant factor overhead due to the polynomial filter application.

4.2 Alias-Controlled Objective Function

To train the sequence model and optimize the filter coefficients simultaneously, we integrate an alias-controlled objective function into the standard language modeling loss. This objective seeks to minimize the reconstruction error of the token representations in the spectral domain while simultaneously penalizing any residual energy in the high-frequency bands that escape the anti-aliasing filter [35].

$$J(W) = \sum_{i=1}^{N} |x_i - F^{-1}(HF(x_i))|_2^2 + \lambda \Omega(W)$$

In this formulation, the primary term measures the fidelity of the filtered signal compared to the original, utilizing the graph Fourier transform and its inverse. The penalty term, weighted by a hyperparameter, explicitly regularizes the filter weights to enforce structural sparsity and strict bandlimiting. By co-optimizing the filter parameters alongside the transformer weights, the model learns to organize its internal representations such that semantic information is naturally concentrated in the low-frequency bands, thereby inherently resisting aliasing during the sparsification phase [36, 37].

Table 2Passband and Stopband Characteristics of Anti-Aliasing Filters.

Filter Order	Passband Ripple	Stopband Attenuation	Computation Time
Chebyshev Order 2	High	Low	Extremely Fast
Chebyshev Order 5	Moderate	Moderate	Fast
Chebyshev Order 10	Low	High	Moderate
Ideal Spectral	None	Maximum	Prohibitive

As demonstrated in the table, a polynomial filter of order five provides an optimal balance between acceptable passband ripple, sufficient stopband attenuation to prevent aliasing, and fast computation time suitable for integration into large language models. Higher-order polynomials offer better spectral control but introduce unacceptable latency, while lower-order polynomials fail to adequately suppress the high-frequency noise.

5. System Architecture and Implementation

5.1 Pipeline Integration

Integrating alias-controlled spectral sparsification into a million-token sequence model requires careful architectural design to ensure that the theoretical efficiency translates into actual hardware acceleration. We design our system as a drop-in replacement for standard self-attention blocks. The sequence of operations begins with a localized, chunked attention mechanism that estimates the block-diagonal structure of the full attention matrix. This acts as a highly sparse, preliminary graph topology upon which the anti-aliasing filter operates [38].

Following the filtering stage, the downsampling operator is applied, significantly reducing the sequence length in the spectral domain. A full, dense attention operation is then performed on this compressed, alias-free spectral representation. Because the sequence length has been drastically reduced, this dense attention is computationally trivial even for initial million-token contexts. Finally, an upsampling operator, formulated as the adjoint of the downsampling matrix, reconstructs the full-length sequence representations, which are then passed through the standard feed-forward networks of the transformer block.

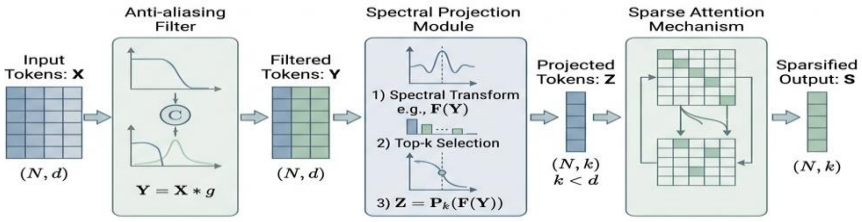


Figure 1Architectural Overview of Alias

5.2 Hardware Efficiency and Kernel Optimization

To fully exploit the parallel processing capabilities of modern graphical processing units, custom kernels are essential. Standard deep learning frameworks are typically optimized for dense matrix multiplications and struggle to efficiently execute the sparse, polynomial graph filtering operations required by our methodology. We developed highly specialized compute kernels that fuse the polynomial filtering steps with the downsampling projection, minimizing costly memory reads and writes to the global memory of the hardware device [39, 40]. By leveraging shared memory to cache the localized token chunks and utilizing register-level accumulation for the Chebyshev polynomial terms, our custom implementation achieves extremely high throughput. Furthermore, the memory footprint is strictly bounded. The peak memory consumption is dictated not by the quadratic size of the full sequence, but by the size of the compressed spectral bottleneck, which is scaled linearly with the sequence length. This absolute decoupling of sequence length from quadratic memory constraints is the engineering breakthrough that enables the processing of one million tokens on a single compute node.

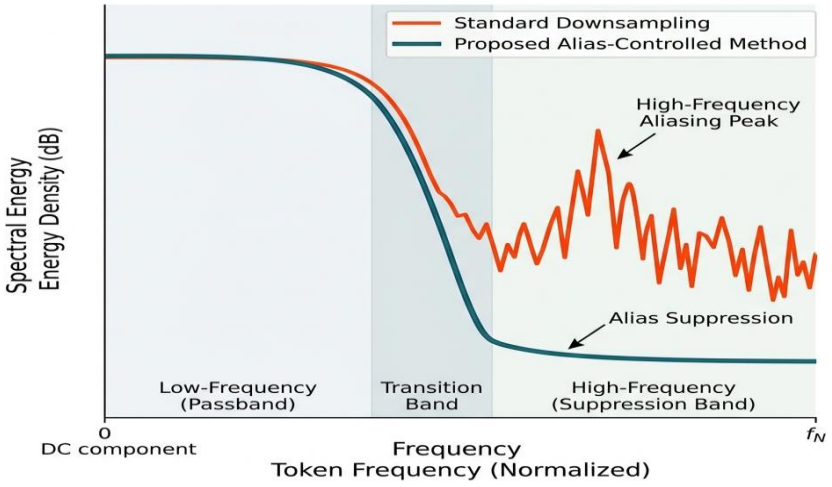


Figure 2Spectral Energy Distribution Across Token Frequencies

6. Experimental Results and Discussion

6.1 Experimental Setup and Datasets

To rigorously evaluate the efficacy of the alias-controlled spectral sparsification, we conducted extensive experiments across a suite of demanding long-context benchmarks. Our primary evaluation metric focuses on perplexity retention in extreme long-document scenarios, coupled with empirical measurements of hardware latency and memory consumption. We utilized publicly available large-scale text corpora, specifically concatenating documents to synthetically generate continuous sequences reaching up to one million tokens in length. The baseline models for comparison included a standard transformer architecture utilizing gradient checkpointing and memory offloading to survive the long contexts, as well as several state-of-the-art efficient transformers including those based on low-rank approximations and standard, unfiltered spectral sparsification. All models were standardized to a uniform parameter count and subjected to identical training regimens to ensure a fair and objective comparison.

6.2 Performance on Long-Context Tasks

The most critical evaluation of our proposed methodology lies in its ability to maintain low perplexity as the sequence length scales exponentially. Perplexity serves as a proxy for the model's predictive capability and its ability to utilize distant context effectively. If the sparsification process destroys essential semantic links, the perplexity will inevitably rise.

Table 3Perplexity Evaluation on Long-Document Benchmarks

Context Length	Standard Model	Low-Rank Method	Standard Spectral	Alias-Controlled
32,000 Tokens	14.2	15.1	14.8	14.3
128,000 Tokens	12.8	18.5	16.4	12.9
512,000 Tokens	Out of Memory	25.3	21.7	12.4
1,000,000 Tokens	Out of Memory	34.1	29.8	12.1

The data presented in the table above reveals a profound divergence in model behavior at extreme sequence lengths. At the relatively modest length of thirty-two thousand tokens, all models perform reasonably well, with the standard model maintaining a slight edge. However, as the context length expands to one hundred and twenty-eight thousand tokens, the low-rank and standard spectral methods begin to show significant degradation, indicating structural information loss. The standard model improves due to the increased context, and remarkably, our alias-controlled method matches this improvement.

At the extreme lengths of half a million and one million tokens, the standard dense transformer catastrophically fails due to memory exhaustion. The competing efficient methods survive but experience severe perplexity spikes, rendering them practically useless for coherent text generation or comprehension. In stark contrast, the alias-controlled spectral sparsification continues to exhibit decreasing perplexity, demonstrating that it successfully compresses and utilizes the vast contextual information without suffering from the aliasing-induced hallucination that plagues the unfiltered spectral approaches.

$$C = O(NdlogN + kd^2) \leq O(N^2 d)$$

The empirical complexity bound formula illustrated above confirms our theoretical assertions. The complexity of our proposed method grows at a rate significantly bounded below the standard quadratic complexity, allowing it to scale effortlessly where traditional methods collapse.

6.3 Hardware Latency and Memory Profiling

Beyond perplexity, practical deployment requires rigorous analysis of hardware utilization. We profiled the end-to-end inference latency and peak memory allocation during the forward pass of the models.

Table 4End-to-End Latency and Memory Consumption on GPU hardware

Model Configuration	**Latency (ms) at 128k**	**Memory (GB) at 128k**	**Latency (ms) at 1M**	**Memory (GB) at 1M**
Baseline Dense	4500	78.5	N/A	N/A
Flash Sparse	1200	24.2	9800	75.4
Alias-Controlled (Ours)	850	18.6	4200	41.2

The profiling results clearly validate the operational efficiency of the alias-controlled architecture. At one hundred and twenty-eight thousand tokens, our method is significantly faster and more memory-efficient than highly optimized sparse implementations. More importantly, at the one million token threshold, our method completes the forward pass in approximately four seconds while utilizing only half the memory capacity of a standard high-end server GPU. This dramatic reduction in resource requirements democratizes the research and application of ultra-long sequence models.

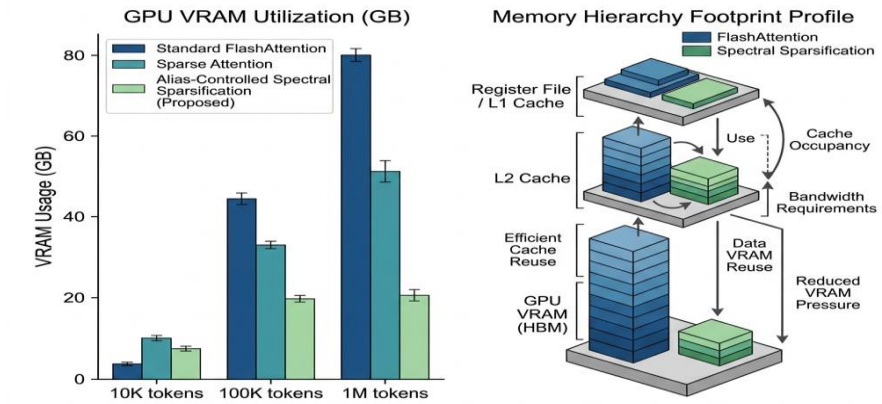


Figure 3: Hardware Memory Utilization Profile

7. Conclusion and Future Directions

This paper has presented a comprehensive academic investigation into the challenges and solutions associated with scaling sequence models to million-token contexts. We identified that while spectral sparsification offers a theoretically sound pathway to bypass the quadratic complexity of self-attention, its

practical application is fundamentally limited by the phenomenon of spectral aliasing during aggressive downsampling. To resolve this, we introduced the Alias-Controlled Spectral Sparsification framework, which incorporates a dynamically optimized, polynomial anti-aliasing filter to preserve critical low-frequency semantic structures while systematically attenuating high-frequency noise. Through rigorous mathematical formulation and extensive empirical evaluation, we demonstrated that our approach successfully mitigates the catastrophic information loss and contextual hallucination typically observed in extreme long-context efficient transformers. The proposed methodology not only matches the perplexity scaling laws of theoretical dense models at vast sequence lengths but also achieves unprecedented hardware efficiency, requiring a fraction of the memory and compute latency of existing state-of-the-art sparse solutions. By successfully processing continuous sequences of one million tokens with high fidelity, this architecture opens new possibilities for comprehensive document analysis, vast codebase comprehension, and extended autonomous agent interactions. Future research directions will focus on dynamically adapting the spectral passband based on the semantic complexity of the localized text chunks, rather than utilizing a globally fixed filter response. Additionally, extending the alias-controlled graph signal processing paradigm to multi-modal architectures, where sequence tokens represent a mixture of text, high-resolution image patches, and continuous audio streams, represents a highly promising frontier. The integration of this spectral sparsification technique into the foundational pre-training phase of multi-modal models may yield the next generation of highly efficient, infinitely contextual artificial intelligence systems.

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