Some Attention is All You Need for Retrieval

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Abstract

We demonstrate complete functional segregation in hybrid SSM-Transformer architectures: retrieval depends exclusively on self-attention layers. Across RecurrentGemma-2B/9B and Jamba-Mini-1.6, attention ablation causes catastrophic retrieval failure (0% accuracy), while SSM layers show no compensatory mechanisms even with improved prompting. Conversely, sparsifying attention to just 15% of heads maintains near-perfect retrieval while preserving 84% MMLU performance, suggesting self-attention specializes primarily for retrieval tasks. We identify precise mechanistic requirements for retrieval: needle tokens must be exposed during generation and sufficient context must be available during prefill or generation. This strict functional specialization challenges assumptions about redundancy in hybrid architectures and suggests these models operate as specialized modules rather than integrated systems, with immediate implications for architecture optimization and interpretability.

1 Introduction

Hybrid SSM-Transformer architectures combine linearly scaling state-space models with quadratically scaling attention mechanisms, promising efficient processing of long sequences without sacrificing performance (Botev et al., 2024; Lieber et al., 2024). While SSMs provide computational efficiency through recurrent state evolution, they exhibit "fuzzy memory"–capturing patterns but struggling with precise retrieval (Waleffe et al., 2024). Attention mechanisms excel at exact retrieval through direct token comparisons (Olsson et al., 2022), motivating architectures that interleave both components layer-wise. Despite their practical success, a fundamental question remains: *do these architectural components develop overlapping capabilities for robustness, or does training induce strict functional segregation?* Understanding this functional organization is essential for both mechanistic interpretability and practical model design. Overlapping capabilities would suggest redundancy, enabling architectural simplification, while strict specialization would indicate task-specific computational delegation.

This distinction has profound implications for interpretability research. Functional segregation would enable targeted analysis of specific capabilities by studying the corresponding specialized components, facilitating a more precise mechanistic understanding. Conversely, overlapping capabilities would require analyzing complex interactions between components, complicating interpretability efforts but potentially revealing emergent computational strategies.

From a practical design perspective, understanding component specialization directly informs architecture optimization. If attention layers specialize exclusively for retrieval while SSM layers handle other language modeling functions, this knowledge enables targeted architectural modifications–such as specialized retrieval modules or attention sparsification strategies–that preserve essential capabilities while reducing computational overhead.

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We present a mechanistic analysis that shines light on this question. Through systematic ablation studies across RecurrentGemma-2B/9B and Jamba-Mini-1.6, we uncover complete functional segregation: **retrieval is exclusive to self-attention layers**, while SSM components contribute nothing to this function. This finding represents a fundamental insight into how hybrid architectures organize their computational capabilities during training.

Our investigation systematically tests three falsifiable hypotheses that probe the mechanistic underpinnings of hybrid architectures:

- **H1:** *Functional Exclusivity*: Retrieval in hybrid architectures depends exclusively on self-attention layers, with SSM layers contributing no retrieval capability. Furthermore, retrieval ability in the SSM layers cannot be recovered through prompting strategies designed to improve retrieval in SSMs.
- **H2:** *Retrieval Specialization*: Self-attention layers specialize primarily for retrieval, such that sparsification preserving minimal retrieval-critical heads maintains general language modeling capabilities while complete ablation causes retrieval-specific failure without broad performance degradation.
- **H3:** *Retrieval Conditions*: Successful retrieval depends on specific mechanistic requirements: needle token exposure during the generation phase and sufficient contextual information available during either prefill or generation phases, where precise attention weight patterns constitute necessary components.

These hypotheses directly address the central research gap by testing whether hybrid architectures exhibit functional redundancy or strict specialization. The systematic testing of these hypotheses through controlled ablation studies across multiple models provides definitive evidence for understanding hybrid model organization.

To rigorously test these hypotheses, we employ entropy-based attention sparsification inspired by Liu et al. (2023) to progressively ablate attention mechanisms while monitoring retrieval performance on the Needle-In-A-Haystack (NIAH) benchmark (Bai et al., 2024). We complement this with Just Read Twice (JRT) prompting (Arora et al., 2024) to attempt recovery of SSM-based retrieval capabilities. Additionally, we assess broader capabilities using GLUE (Wang et al., 2019) and MMLU (Hendrycks et al., 2020) benchmarks to ensure that observed retrieval-specific effects do not indicate general performance degradation.

Our analysis reveals three critical insights: **(1)** Across model scales and architectural variants, as few as 15% of attention heads maintain near-perfect retrieval while complete ablation causes catastrophic failure, demonstrating that SSM layers do not contribute to retrieval. **(2)** This sparsification preserves 84% performance on MMLU, isolating retrieval without broadly degrading model performance, thereby revealing opportunities for more effective model design. **(3)** Successful retrieval requires specific mechanistic conditions–needle token exposure during generation plus sufficient contextual information during prefill and generation phases–establishing precise requirements for the attention-based retrieval mechanism.

These findings provide the first definitive evidence of complete functional segregation in hybrid architectures, revealing that training induces strict specialization. This understanding enables targeted optimization strategies, more precise interpretability research, and informed design of future hybrid architectures that leverage the distinct strengths of each component type.

2 Methods

2.1 Models and Experimental Setup

We investigate functional segregation in hybrid SSM-Transformer architectures through systematic ablation studies across three models: RecurrentGemma-2B (RG-2B), RecurrentGemma-9B (RG-9B), and Jamba-Mini-1.6 (Jamba). These models represent diverse architectural approaches to hybrid design, varying in size, attention mechanism implementation, and component organization.

RG-2B contains 2B parameters across 26 layers organized as eight repetitions of the pattern "2× SSM, 1× Attention" followed by two SSM layers, with 10 attention heads per attention layer. RG-9B extends this architecture to 9B parameters across 38 layers (12 pattern repetitions) with 16 heads per attention layer. Both RecurrentGemma models employ sliding window attention with a 2048-token window. Jamba represents a distinct architectural approach with 51B total parameters (12B active during inference) organized across 32 layers following the pattern "3× SSM, 1× Attention, 4× SSM". Unlike RecurrentGemma, Jamba utilizes global attention with 32 heads per layer and incorporates Mixture of Experts (MoE) layers that substitute standard MLPs in every other layer. This architectural diversity enables testing whether functional segregation emerges consistently across different hybrid designs. All experiments employ a unified experimental framework implemented through ManipuLatte[2], our custom library providing consistent interfaces for attention manipulation across architectures. Models were tested with batch size of one, with prompt lengths up to 4096 tokens distributed across ten lengths and ten needle depths (100 prompts total), following the protocol established by Zani et al. (2025). Complete model specifications and computational resources are detailed in Appendix A.

2.2 Attention Sparsification Method

Inspired by the contextual sparsity introduced by Liu et al. (2023), we employ a simpler entropy-based top-k sparsification to systematically ablate attention mechanisms while preserving the most informative heads. For each attention head, we calculate the entropy of attention weight distributions as:

$$H(A) = -\sum_t a_t \times \log_2(a_t) \tag{1}$$

where A represents the attention weight vector and a_t denotes the attention weight for token t. Lower entropy indicates more focused attention patterns, suggesting greater information content and specificity in the attention mechanism.

During sparsification, we retain only the k attention heads with the lowest entropy across all layers, ablating the remaining heads by setting their corresponding values in the attention output to zero. This approach preserves heads that exhibit the most decisive attention patterns while removing those with more uniform (higher entropy) distributions. We test values of $k \in [0, N]$ where N equals the total number of heads per layer (10 for RG-2B, 16 for RG-9B, 32 for Jamba), with $k = 0$ representing complete attention ablation and $k = N$ representing the unmodified model. Unless otherwise specified, we apply sparsity only during generation and keep $k = N$ fixed during prefill. See Section 2.5 for more details.

2.3 Attempting to Improve SSM Retrieval with Just Read Twice

To test whether SSM layers can recover retrieval capabilities when attention is ablated, we apply Just Read Twice (JRT) prompting (Arora et al., 2024) for severely sparsified models ($k \in \{0, 1, 2\}$). JRT repeats the context and question to potentially activate latent retrieval mechanisms in SSM layers, providing a stringent test of functional exclusivity.

2.4 Evaluation Benchmarks

We employ three complementary benchmarks to isolate retrieval-specific effects from general performance degradation. The Needle-In-A-Haystack (NIAH) benchmark (Bai et al., 2024) directly measures retrieval capabilities by requiring models to extract specific information (the “needle”) from contexts filled with irrelevant text. Complete NIAH specifications and scoring rubrics are provided in Appendix B.

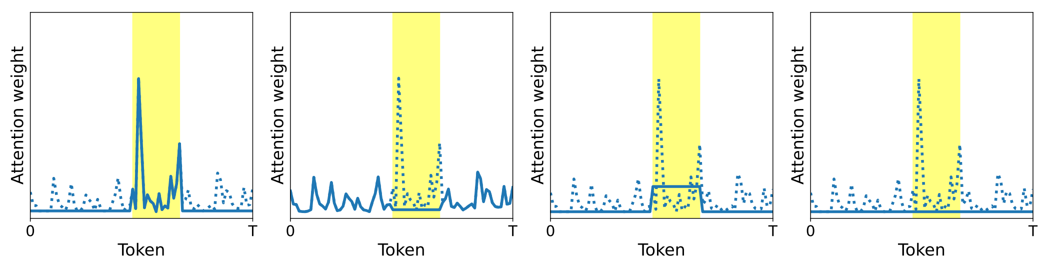
To assess broader language modeling capabilities, we employ GLUE (Wang et al., 2019) and MMLU (Hendrycks et al., 2020) benchmarks using the LM-Evaluation-Harness (Gao et al., 2024). GLUE evaluates fundamental natural language understanding through nine tasks, including sentiment analysis and textual entailment (zero-shot configuration). MMLU tests advanced reasoning across 57 subjects spanning STEM, humanities, and social sciences (five-shot configuration). Both benchmarks evaluate using the log-likelihood of multiple-choice options after the prefill stage, enabling assessment of how attention sparsification affects general capabilities versus retrieval-specific functions.

[2] Available at `https://github.com/lamalunderscore/manipulatte`

2.5 Attention Manipulation Techniques

To understand the mechanistic requirements for successful retrieval, we implement four targeted attention weight manipulation techniques applied during different inference phases. These manipulations isolate specific components of the attention mechanism to identify necessary conditions for retrieval.

The *Only* manipulation nullifies attention weights for all tokens except needle tokens, which retain their original values, isolating the direct attention to retrieval targets. The *Omit* manipulation inverts this by nullifying only needle token weights while preserving all others, testing whether contextual information alone suffices for retrieval. The *Binary* manipulation extends *Only* by assigning uniform average weights across needle tokens, testing whether precise weight values or merely token exposure drives retrieval. The *Null* manipulation ablates all attention weights, equivalent to $k = 0$ sparsification. See Figure 1 for a visual representation.



(a) Only (b) Omit (c) Binary (d) Null

Figure 1: Simplified representation of manipulation methods. Original attention weights (dotted blue), modified weights (solid blue), and needle tokens (yellow highlight).

We test all combinations of prefill and generation manipulations (denoted as "Generation-Prefill", e.g., "Omit-Null" applies *Omit* during generation and *Null* during prefill), excluding *Null* during generation alone as this equals complete sparsification. This systematic manipulation reveals the precise conditions required for the attention-based retrieval mechanism to function successfully.

3 Retrieval Depends Exclusively on Self-Attention

Testing H1 (functional exclusivity) requires demonstrating that retrieval depends exclusively on self-attention layers with no SSM contribution, even under prompting strategies designed to enhance SSM performance. We systematically vary attention sparsification levels while monitoring retrieval performance, complemented by Just Read Twice (JRT) prompting (Arora et al., 2024) to attempt recovery of potential latent SSM retrieval capabilities.

3.1 Results

As seen in Figure 2, all three models showed distinct but similar behaviors for sparsification. We refered to the model versions that are only sparsified during the generation stage as *generation versions*, and to the versions that are sparsified during both stages as *prefill versions*.

All models maintained high accuracy until model-specific thresholds, then showed gradual degradation before catastrophic failure. Jamba sustained 100% accuracy until $k = 27$, then declined to $k = 6$ where it sharply dropped to zero. RG-9B degraded from $k = 16$ to $k = 3$ before failing completely at $k = 2$. RG-2B's generation version remained stable until $k = 1$ where it collapsed, while its prefill version immediately dropped to 20% accuracy. Critically, all models exhibited a final tipping point ($k \in \{1, 2, 3, 4\}$ for generation versions) where accuracy abruptly fell to zero–this threshold correlated with attention head count (32, 16, and 10 heads respectively).

Following Figure 3, applying JRT did not recover retrieval capabilities at low k. See Appendix C for a comparison between retrieval maps for standard and JRT prompting.

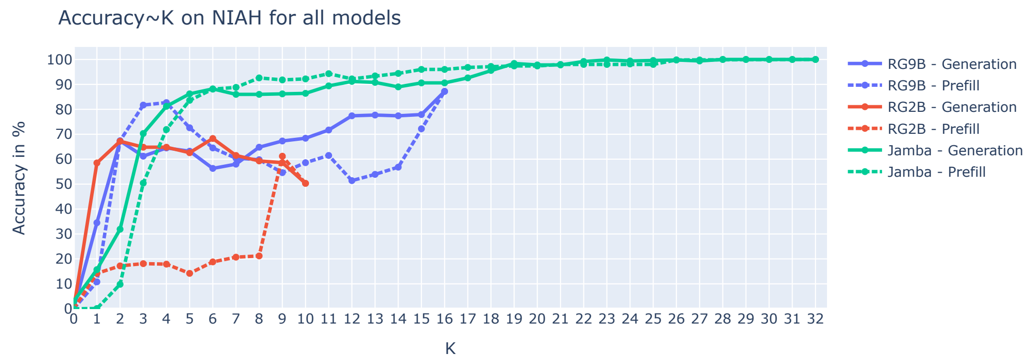


Figure 2: Accuracy as a function of k in top-k sparsification on standard NIAH for *generation* and *prefill versions*. Accuracy was approximated by the average score across all 100 prompts, relative to the maximum score (5). Note that scoring was neither linear nor continuous (see Table 2 for interpretation guidance). Read from right to left for increasing sparsity.

3.2 Discussion

Retrieval failed for all models at $k = 0$, which confirmed that the findings made by Zani et al. (2025) also hold for other hybrid LLMs. However, all three models showed slightly different tipping points in generation versions, after which the accuracy started to decrease drastically: $k = 4$ for Jamba, $k = 2$ for RG-9B, and $k = 1$ for RG-2B. Still, the overall behavior is similar across all three models. Note that our results showed the tipping point for RG-2B at $k = 1$, whereas Zani et al. (2025) identified this tipping point to be around $k = 2$. This difference can be attributed to our improved scoring method and prompt structure.

Regarding the prefill versions, the difference in behaviors was striking, especially prominent in the behavior of RG-2B. While the RG-2B prefill version failed even at low sparsification levels, the Jamba prefill version performed almost identically to its generation version. It seems as though the effect size of prefill sparsification reduces with increasing model size.

It is important to consider the impact of sparsification on the internals of a model. Any manipulation of the computations during a forward pass will alter the residual stream and therefore yield, compared to the original activations, an imperfect version of all downstream activations. This means that every layer activation after the first manipulation is imperfect, and every further manipulation likely increases the magnitude of the effect. This also means that every query-, key- and value-projection is imperfect. Since the RG models used a cache for the values of key- and value-projections (kv-cache) to optimize inference time, the query-projection will use the faulty cached key- and value-projections for every subsequent forward pass during that inference run, increasing the impact of the manipulation. Especially important for this cache is the prefill stage, as the cache gets filled with all projections of the prompt tokens. Jamba was not set up to use this caching mechanism. Hence, we would expect the RG models to be impacted more by prefill sparsification.

Since all models failed to retrieve the needle at $k = 0$, and applying JRT did not recover this retrieval capability, this provides further strong evidence that retrieval in hybrid LLMs is exclusively implemented through self-attention layers. This also further solidifies the hypothesis that during training, only self-attention layers learn the retrieval function, so much so that SSM layers do not even develop the common *fuzzy memory* (Waleffe et al., 2024).

Future work could compare state transition matrices between pure and hybrid SSM variants to uncover how retrieval mechanisms differ when attention is available versus absent, potentially revealing fundamental SSM retrieval strategies.

4 Self-Attention Specializes for Retrieval

Testing H2 (retrieval specialization) requires demonstrating that self-attention layers specialize primarily for retrieval, such that sparsification preserving minimal retrieval-critical heads maintains general capabilities. We evaluate this through systematic benchmarking on GLUE and MMLU at different sparsification levels.

We test three configurations on Jamba: base (unmodified), optimally sparsified ($k = 5$, the minimal prefill sparsification maintaining near-perfect retrieval from Section 3), and fully ablated ($k = 0$, complete attention removal). This comparison isolates the impact of attention sparsification on general versus retrieval-specific capabilities. We apply sparsity during prefill, as the benchmark answers are evaluated by log-likelihood without generation.

4.1 Results

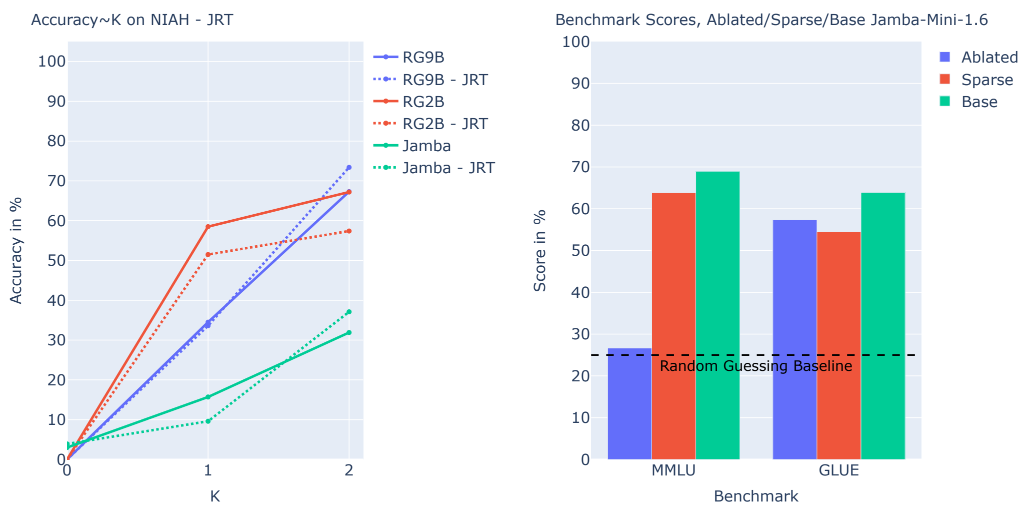


Figure 3: **Left**: Accuracy as a function of k in top-k sparsification on NIAH with and without JRT applied, for all models in the generation version. Accuracy was approximated by the average score across all 100 prompts, relative to the maximum score (5). Note that scoring was neither linear nor continuous (see Table 2 for interpretation guidance). Read from right to left for increasing sparsity. **Right:** Scores for Jamba-Mini-1.6, in an ablated configuration ($k = 0$), a sparse configuration ($k = 5$), and the base configuration, on GLUE and MMLU.

Figure 3 shows the average achieved scores per benchmark, per model configuration. See Appendix D for subtask results.

On GLUE, the base configuration of Jamba performed best, but the ablated and sparsified versions only scored slightly lower (6.6 and 9.1 points, respectively). Although only marginally, the ablated version scored higher than the sparse version (2.8 points). On MMLU, the base configuration performed best again. The sparse version only scored six points below the base configuration, whereas the ablated version scored around 42 points below the base configuration.

4.2 Discussion

The results provide evidence that the retrieval capability of self-attention layers can be isolated through sparsification. However, the effect of sparsification depends significantly on the complexity and nature of the evaluated task.

The big difference in the effect of sparsification and ablation between MMLU and GLUE highlights the necessity for retrieval capabilities for more difficult language modeling tasks, whereas general language capabilities do not depend on retrieval to such a degree.

Still, the sparsified configuration performing worse than the ablated configuration in GLUE hints at a suboptimal sparsification method. Ablating the wrong attention heads can lead to broken retrieval functions, effectively introducing noise or even facilitating a misleading information flow. Instead of investigating attention heads behaviorally, future iterations could structurally investigate attention heads through an offline analysis that examines the weights of different circuits in the self-attention architecture, as performed by Olsson et al. (2022). Such an analysis could provide insights into which heads are implementing which kind of capabilities and functions before running inference. This way, instead of dynamically choosing the attention heads to ablate at run time, a model could be sparsified statically, based on the characteristics of different heads, and with more care.

5 Mechanistic Requirements for Retrieval

Testing H3 (retrieval conditions) requires identifying the specific mechanistic requirements for successful retrieval. We systematically manipulate attention weights to isolate necessary conditions: needle token exposure and contextual information availability during different inference phases.

We apply the four manipulation techniques described in Section 2.5 (*Only*, *Omit*, *Binary*, *Null*) to RG-2B without sparsification ($k = N$), testing all combinations of prefill and generation manipulations. This approach reveals which attention components are mechanistically necessary for retrieval.

5.1 Results

		Generation			
		Keep	Omit	Only	Binary
Prefill	Keep	50.3%	3.7%	**<u>85.7%</u>**	3.7%
	Omit	63.0%	0.0%	53.0%	0.0%
	Only	**70.6%**	0.1%	18.2%	0.1%
	Binary	0.0%	0.0%	0.0%	0.0%
	Null	<u>68.8%</u>	0.0%	17.0%	0.0%

Table 1: NIAH results for all tested manipulation combinations on RecurrentGemma-2B.Marked as **<u>overall best</u>**, **second best** and <u>third best</u>

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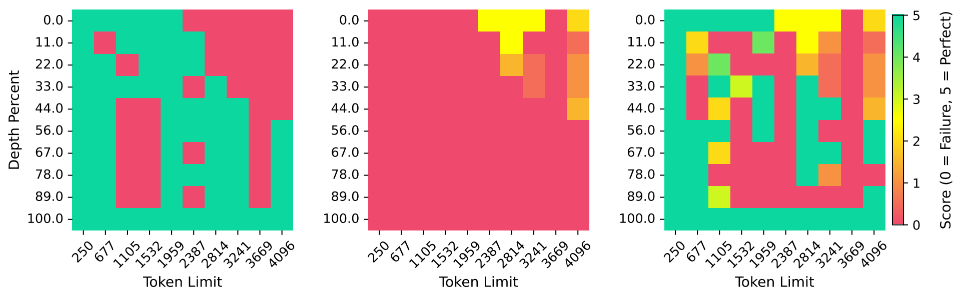
Table 1 gives an overview of the accuracies scored in NIAH for different combinations of prefill and generation manipulation. Omitting the needle tokens during generation led to a drastic drop in accuracy, with Omit-Keep reaching 3.7% accuracy, and all other combinations scoring zero or close to zero percent accuracy. Applying the Binary method during generation yielded the same accuracies as applying the Omit method; all combinations applying Binary during prefill scored zero percent accuracy. The combinations Keep-Omit, Keep-Only, and Keep-Null all improved the accuracy relative to the base configuration, with 63.0%, 70.6%, and 68.8%, respectively. When only keeping the needle tokens during prefill, not manipulating the prefill, or omitting the needle tokens also improved the scores relative to the base configuration, with 85.7% and 53.0%, respectively. Only-Keep reached the highest score across all combinations. Note that every sparsification combination that did not severely reduce retrieval capabilities yielded better scores than the base model (Keep-Keep).

For a complete overview of all retrieval maps, see Appendix E.

5.2 Discussion

The results suggest that successful retrieval necessitates, firstly, exposure of the needle tokens during generation, and secondly, exposure of tokens that provide sufficient context either during prefill or during generation. The first point is obvious from the results when applying Omit during generation. Every combination, including Omit-Keep, fails retrieval. To deduce the second point, the key combinations to look at are Only-Omit and Only-Only, as well as Keep-Omit, Keep-Only, and Keep-Null. Only-Omit shows that, even when only exposing the needle tokens during generation, only exposing the structure around the needle during prefill suffices to facilitate successful (above baseline) retrieval capabilities; when not exposing the structure during prefill, like in Only-Only, retrieval fails. The other three combinations, especially Keep-Null, show that the tokens exposed during prefill are irrelevant, likely because enough tokens are exposed during generation.



(a) Keep-Omit (b) Omit-Keep (c) Keep-Keep (Base)

Figure 4: Retrieval maps for RG-2B on NIAH with the manipulations Keep-Omit, Omit-Keep, and Keep-Keep applied. The x-axis shows the used prompt length, the y-axis the depth of the needle, 0% being the very end of the prompt and 100% being the very beginning of the prompt.

Additionally, the low accuracy scores when applying Binary showed that the values of the attention weights are important for successful retrieval. It is not enough to expose necessary tokens more than unnecessary ones, but the exact structure of and relations between the attention weights matter.

Investigating the retrieval maps of different combinations revealed further details, refining the previous hypothesis. The retrieval maps for Keep-Omit (Figure 4a) and Omit-Keep (Figure 4b) complement each other to make up an improved version of Keep-Keep (Figure 4c). This means that Omit-Keep, which was previously labeled as a retrieval failure, was not a failure but only a partial success.

The partial retrieval success in Figure 4b aligns with RecurrentGemma's 2048-token sliding window–successful retrievals occur only when needles fall within this window during generation. Retrieval beyond the window requires prefill exposure, suggesting the kv-cache preserves implicit retrieval information even when tokens exit the active attention window. See Figure 10 for complete retrieval maps.

Since the Binary method yielded such detrimental results, we examined the outputs of corresponding combinations. The outputs showed that when Binary was applied during prefill, the generated tokens were mostly nonsensical. When Binary was applied during generation, the generated tokens made sense, but were off topic. See Appendix F for a selection of pearls of wisdom generated by confused hybrid models.

Applying Binary during prefill likely has a similar effect on the kv-cache as sparsifying during the prefill stage (see Section 3.2), producing nonsensical tokens during generation. This would also explain why applying Binary only during generation did not result in such catastrophic failures, as the kv-cache was prefilled with unmanipulated keys and values.

Overall, the Binary method was not thoroughly investigated before employing it, but rather it was implemented in a way that most efficiently applied the idea of unifying attention weights across a range of tokens. For example, upon examining attention weights for the first activations in the generation stage, it became obvious that the range of the needle tokens always started with a large peak in the weights on the exact token that would have to be predicted (also visible in Figure 1). The behavior of the attention weights throughout the generation process was not further investigated. This peak likely moves across the range of needle tokens, always being located on the token corresponding to the correct prediction. A behavior like this would mean that the method used to apply the idea of unifying and binarizing attention weights was inadequate. This limitation could be overcome in future research.

6 Conclusion

We established complete functional segregation in hybrid SSM-Transformer architectures: retrieval depends exclusively on self-attention layers while SSMs handle general language capabilities. Across RecurrentGemma and Jamba models, attention ablation caused catastrophic retrieval failure (0% accuracy) with no SSM compensation, even under specialized prompting. Yet sparsifying to just 15% of attention heads preserved near-perfect retrieval and 84% MMLU performance, revealing precise functional specialization. Our entropy-based sparsification method showed suboptimal performance in some cases, indicating the need for more sophisticated approaches such as structural circuit analysis of the self-attention mechanism, as was performed by Olsson et al. (2022).

This functional segregation in hybrid models enables immediate practical optimizations–targeted sparsification, specialized retrieval modules, and component-specific deployment strategies. Future work may explore whether this specialization emerges from architectural constraints or training dynamics, and whether lightweight retrieval-specific mechanisms could replace full attention layers. Understanding this functional division advances both mechanistic interpretability and efficient architecture design, suggesting hybrid models operate as task-specific specialists rather than fully integrated systems.

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References

Simran Arora, Aman Timalsina, Aaryan Singhal, Benjamin Spector, Sabri Eyuboglu, Xinyi Zhao, Ashish Rao, Atri Rudra, and Christopher Ré. Just Read Twice: closing the recall gap for recurrent language models, 2024. URL http://arxiv.org/abs/2407.05483. arXiv:2407.05483 [cs].

Yushi Bai, Xin Lv, Jiajie Zhang, Yuze He, Ji Qi, Lei Hou, Jie Tang, Yuxiao Dong, and Juanzi Li. LongAlign: A Recipe for Long Context Alignment of Large Language Models, 2024. URL https://arxiv.org/abs/2401.18058.

Aleksandar Botev, Soham De, Samuel L. Smith, Anushan Fernando, George-Cristian Muraru, Ruba Haroun, Leonard Berrada, Razvan Pascanu, Pier Giuseppe Sessa, Robert Dadashi, Léonard Hussenot, Johan Ferret, Sertan Girgin, Olivier Bachem, Alek Andreev, Kathleen Kenealy, Thomas Mesnard, Cassidy Hardin, Surya Bhupatiraju, Shreya Pathak, Laurent Sifre, Morgane Rivière, Mihir Sanjay Kale, Juliette Love, Pouya Tafti, Armand Joulin, Noah Fiedel, Evan Senter, Yutian Chen, Srivatsan Srinivasan, Guillaume Desjardins, David Budden, Arnaud Doucet, Sharad Vikram, Adam Paszke, Trevor Gale, Sebastian Borgeaud, Charlie Chen, Andy Brock, Antonia Paterson, Jenny Brennan, Meg Risdal, Raj Gundluru, Nesh Devanathan, Paul Mooney, Nilay Chauhan, Phil Culliton, Luiz Gustavo Martins, Elisa Bandy, David Huntsperger, Glenn Cameron, Arthur Zucker, Tris Warkentin, Ludovic Peran, Minh Giang, Zoubin Ghahramani, Clément Farabet, Koray Kavukcuoglu, Demis Hassabis, Raia Hadsell, Yee Whye Teh, and Nando de Frietas. RecurrentGemma: Moving Past Transformers for Efficient Open Language Models, August 2024. URL http://arxiv.org/abs/2404.07839. arXiv:2404.07839 [cs].

Leo Gao, Jonathan Tow, Baber Abbasi, Stella Biderman, Sid Black, Anthony DiPofi, Charles Foster, Laurence Golding, Jeffrey Hsu, Alain Le Noac'h, Haonan Li, Kyle McDonell, Niklas Muennighoff, Chris Ociepa, Jason Phang, Laria Reynolds, Hailey Schoelkopf, Aviya Skowron, Lintang Sutawika, Eric Tang, Anish Thite, Ben Wang, Kevin Wang, and Andy Zou. The Language Model Evaluation Harness, 07 2024. URL https://zenodo.org/records/12608602.

Dan Hendrycks, Collin Burns, Steven Basart, Andy Zou, Mantas Mazeika, Dawn Song, and Jacob Steinhardt. Measuring Massive Multitask Language Understanding. *CoRR*, abs/2009.03300, 2020. URL https://arxiv.org/abs/2009.03300.

Opher Lieber, Barak Lenz, Hofit Bata, Gal Cohen, Jhonathan Osin, Itay Dalmedigos, Erez Safahi, Shaked Meirom, Yonatan Belinkov, Shai Shalev-Shwartz, Omri Abend, Raz Alon, Tomer Asida, Amir Bergman, Roman Glozman, Michael Gokhman, Avashalom Manevich, Nir Ratner, Noam Rozen, Erez Shwartz, Mor Zusman, and Yoav Shoham. Jamba: A Hybrid Transformer-Mamba Language Model, July 2024. URL http://arxiv.org/abs/2403.19887. arXiv:2403.19887 [cs].

Zichang Liu, Jue Wang, Tri Dao, Tianyi Zhou, Binhang Yuan, Zhao Song, Anshumali Shrivastava, Ce Zhang, Yuandong Tian, Christopher Re, and Beidi Chen. Deja Vu: Contextual Sparsity for Efficient LLMs at Inference Time. In *Proceedings of the 40th International Conference on Machine Learning*, pp. 22137–22176. PMLR, July 2023. URL https://proceedings.mlr.press/v202/liu23am.html. ISSN: 2640-3498.

Catherine Olsson, Nelson Elhage, Neel Nanda, Nicholas Joseph, Nova DasSarma, Tom Henighan, Ben Mann, Amanda Askell, Yuntao Bai, Anna Chen, Tom Conerly, Dawn Drain, Deep Ganguli, Zac Hatfield-Dodds, Danny Hernandez, Scott Johnston, Andy Jones, Jackson Kernion, Liane Lovitt, Kamal Ndousse, Dario Amodei, Tom Brown, Jack Clark, Jared Kaplan, Sam McCandlish, and Chris Olah. In-context learning and induction heads. *Transformer Circuits Thread*, 2022. https://transformer-circuits.pub/2022/in-context-learning-and-induction-heads/index.html.

Roger Waleffe, Wonmin Byeon, Duncan Riach, Brandon Norick, Vijay Korthikanti, Tri Dao, Albert Gu, Ali Hatamizadeh, Sudhakar Singh, Deepak Narayanan, Garvit Kulshreshtha, Vartika Singh, Jared Casper, Jan Kautz, Mohammad Shoeybi, and Bryan Catanzaro. An Empirical Study of Mamba-based Language Models, June 2024. URL http://arxiv.org/abs/2406.07887. arXiv:2406.07887 [cs].

Alex Wang, Amanpreet Singh, Julian Michael, Felix Hill, Omer Levy, and Samuel R. Bowman. GLUE: A Multi-Task Benchmark and Analysis Platform for Natural Language Understanding, 2019. URL https://arxiv.org/abs/1804.07461.

Davide Zani, Felix Michalak, and Steven Abreu. Contextual Sparsity as a Tool for Mechanistic Understanding of Retrieval in Hybrid Foundation Models. In *Sparsity in LLMs (SLLM): Deep Dive into Mixture of Experts, Quantization, Hardware, and Inference*, 2025. URL https://openreview.net/forum?id=TGWzg86kYv.

A Model Specifications

We used three different models: RecurrentGemma-2B (RG-2B), RecurrentGemma-9B (RG-9B), and Jamba-Mini-1.6 (Jamba).

RG-2B was used by Zani et al. (2025) as a comparatively small hybrid LLM that is easy to run. We used this model to provide comparability to previous results. This model consists of 2.03B parameters (excluding embedding parameters) spread across 26 layers, being eight repetitions of the pattern "2× SSM, 1× Attention" followed by two SSM layers. Each attention layer hosts ten attention heads.

RG-9B was used as a model of a larger size that is comparable to RG-2B. RG-9B and RG-2B are of the same structure and architecture, just that RG-9B is bigger in scale with 7.53B parameters spread across 38 layers, being 12 repetitions of the pattern "2× SSM, 1× Attention" followed by two SSM layers. The attention layers of RG-9B host 16 heads each.

Both RG models use sliding window attention with a sliding window size of 2048.

Jamba was used as a model of different architecture to compare to the RG models. Jamba uses global attention and Mixture of Experts (MoE) layers that systematically substitute Multilayer Perceptrons (MLPs). MoE layers are sparse alternatives to MLPs that only use a fraction of parameters during inference, effectively reducing the memory footprint of a model. Jamba consists of 51.03B total parameters (excluding embedding parameters), of which only 12B are active during inference, spread across 32 layers in a pattern of "3× SSM, 1× Attention 4× SSM". Each attention layer hosts 32 attention heads.

These three models built a diverse basis for experimental results, differing in their parameter sizes, attention implementation, and surrounding architecture.

All experiments were conducted on a high-performance cluster, utilizing a maximum of two AMD Zen 3 EPYC 7763 processors, eight NVIDIA A100 (40 GB HBM2) graphics cards, and 1024 GB of memory.

B NIAH Benchmark Implementation Details

The Needle-In-A-Haystack (NIAH) benchmark is built on the implementation by Bai et al. (2024). The task in NIAH is to retrieve a specific sentence from a context that is filled with irrelevant text. The to-be-retrieved information is called the *needle*, and the whole context, including the irrelevant text and the needle, is called the *haystack*. The benchmark evaluates the ability of a model to retrieve the needle from the haystack for multiple prompts of different lengths. Through strategic prompt generation, this benchmark can yield retrieval maps that unveil the retrieval performance of a model, depending on the position of the needle and the size of the haystack. See Figure 4 for examples of such a retrieval map. Following Bai et al. (2024), we used the same collection of essays from Paul Graham[3] to generate the haystack, as well as the same needle.

The needle was "The best thing to do in San Francisco is eat a sandwich and sit in Dolores Park on a sunny day". The retrieval question was "What is the best thing to do in San Francisco?".

We chose a maximum prompt length of 4096 tokens. For each tokenizer, 100 prompts were generated: ten prompt lengths at ten depths.

As an improvement over the scoring method used by Zani et al. (2025), which was a simple binary string matching evaluation, we implemented granular scoring. While still based on string matching, partial matches were allowed to yield partial scores. For each keyword of the needle that was present in the output string, the score was increased. The scores for all partial keywords added up to three. If the full needle string matched, the score was set to five. While examining outputs from test experiments on Jamba, we stumbled across a curious phenomenon: the grammatically imperfect needle was predicted with corrected grammar, thereby only scoring three points. To visualize this phenomenon, we added a rule: if the needle was predicted with corrected grammar, the score was set to four. See Table 2 for concrete strings and their scoring behavior.

[3]All essays can be found in their original form at https://www.paulgraham.com/articles.html, and are also part of the GitHub repository for this project at https://github.com/lamalunderscore/retrieval-in-hybrid-ssms.

Keyword	Score
"eat a sandwich"	increase by 1.0
"Dolores Park"	increase by 0.5
"sit in Dolores Park"	increase by 0.5
"sunny day"	increase by 1.0
"is to eat a sandwich and sit in Dolores Park on a sunny day"	set to 4.0
"The best thing to do in San Francisco is eat a sandwich and sit in Dolores Park on a sunny day"	set to 5.0

Table 2: Granular scoring system for NIAH evaluation. Keyword strings used in the evaluation of retrieval success, and their influence on the score. Notice the grammatical imperfection in the full needle string (last row).

B.1 Prompt templates used in NIAH

For base models that were not instruction-tuned, we used the following template to style the prompts:

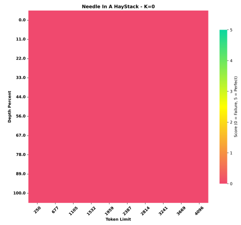
```
CONTEXT:
<haystack>

QUESTION:
<retrieval question>

ANSWER: Here is the most relevant sentence in the context:
```

For instruction-tuned models, we changed the template to:

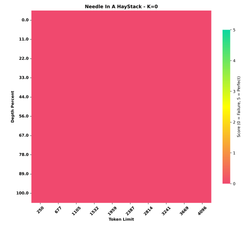
```
CONTEXT:
<haystack>

QUESTION:
<retrieval question> Output the most relevant sentence in the context, word by word!
```

C Comparing retrieval maps for JRT and standard NIAH

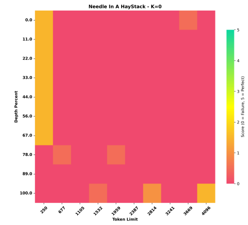
In Section 3, we are also testing if applying JRT improves retrieval capabilities for top-k-sparsified RG-2B, RG-9B and Jamba. Figure 5, 6, and 7 compare the retrieval maps of standard NIAH and JRT-applied NIAH on the same k on all models. Refer to Figure 4 for an explanation of the axes.



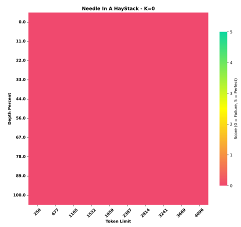
(a) RG-2B - Base



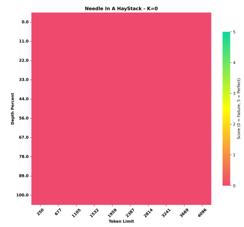
(b) RG-9B - Base



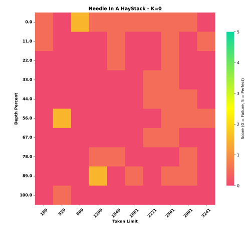
(c) Jamba - Base



(d) RG-2B - JRT

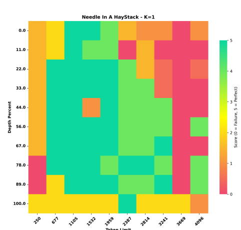


(e) RG-9B - JRT

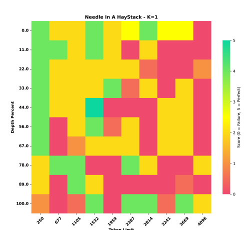


(f) Jamba - JRT

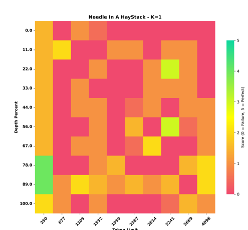
Figure 5: Retrieval maps for RG-2B, RG-9B and Jamba at $k = 0$ on NIAH with and without JRT applied.



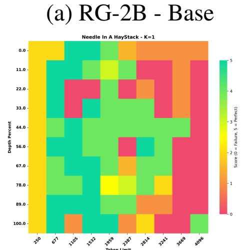
(a) RG-2B - Base



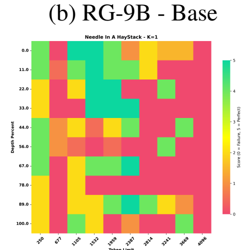
(b) RG-9B - Base



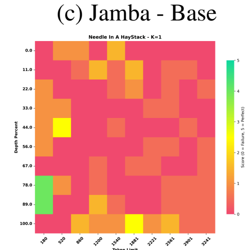
(c) Jamba - Base



(d) RG-2B - JRT

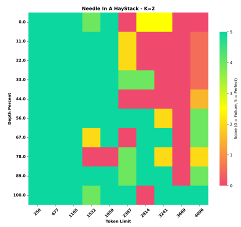


(e) RG-9B - JRT

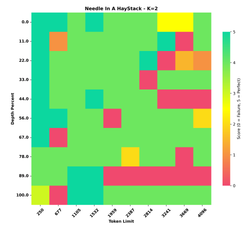


(f) Jamba - JRT

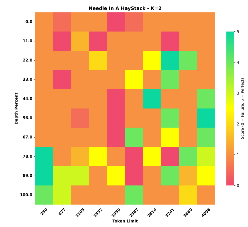
Figure 6: Retrieval maps for RG-2B, RG-9B and Jamba at $k = 1$ on NIAH with and without JRT applied.



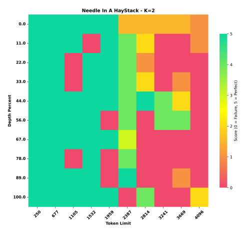
(a) RG-2B - Base



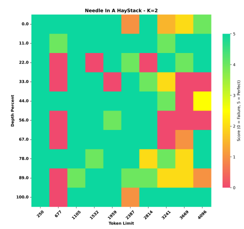
(b) RG-9B - Base



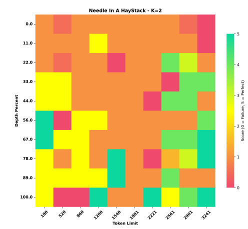
(c) Jamba - Base



(d) RG-2B - JRT



(e) RG-9B - JRT



(f) Jamba - JRT

Figure 7: Retrieval maps for RG-2B, RG-9B and Jamba at $k = 2$ on NIAH with and without JRT applied.

D LME Benchmark

In Section 4, we tested Jamba using LME. It is an instruction-tuned model, so evaluation was run with the `apply_chat_template` and `fewshot_as_multiturn` flags. Figures 8 and 9 show the performance of Jamba in the ablated, sparsified and base version per subtask on GLUE and MMLU.

Figure 8: GLUE benchmark Sub Task scores of the ablated ($k = 0$), sparse ($k = 5$) and base configuration.

E Retrieval maps for attention weight manipulation

In Section 5, we systematically manipulated the attention weights in RG-2B during NIAH benchmarks. Figure 10 shows the retrieval maps of those benchmarks, structured in the same way as Table 1 for easy comparison.

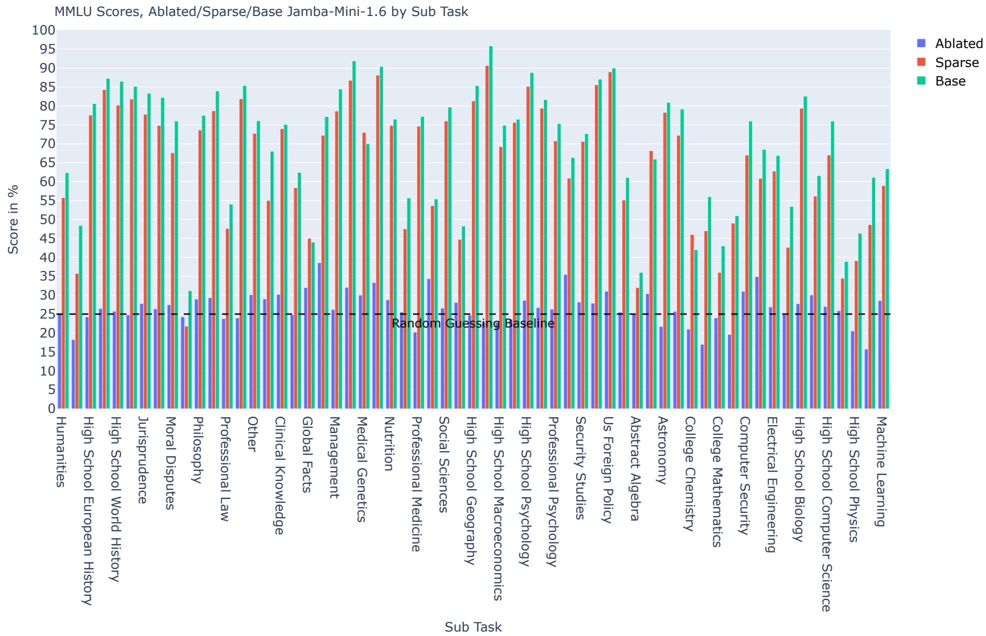


Figure 9: MMLU benchmark Sub Task scores of the ablated ($k = 0$), sparse ($k = 5$) and base configuration.

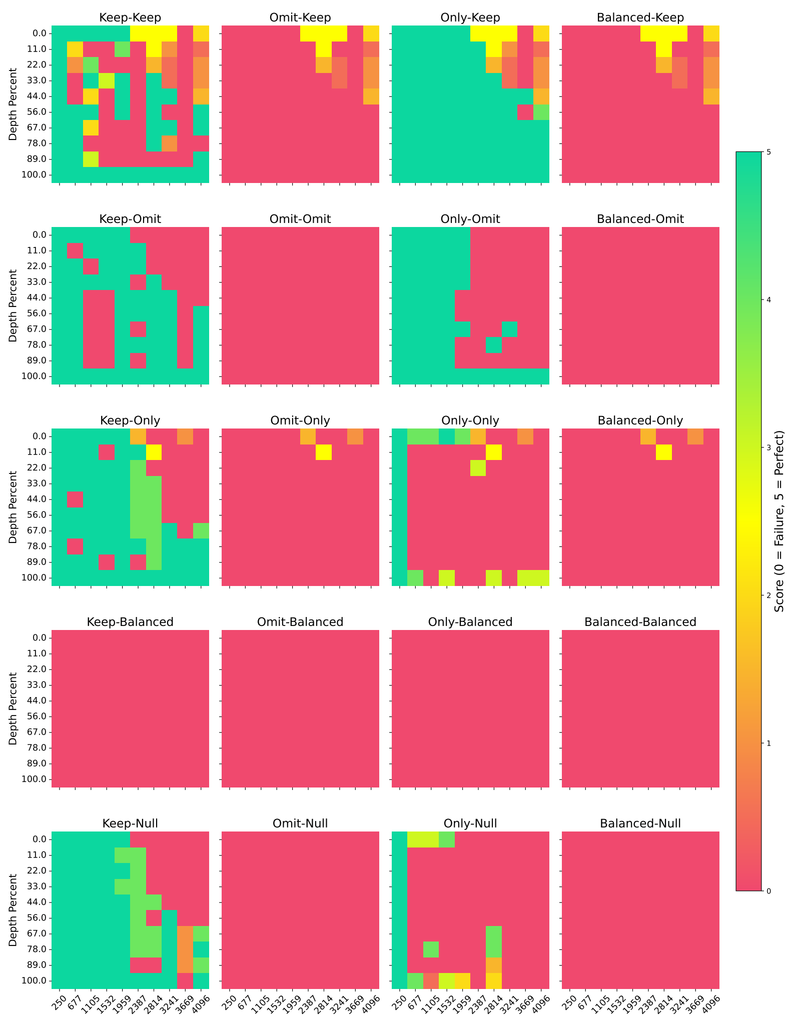


Figure 10: Retrieval maps for all manipulation combinations used in Section 5.

F Pearls of Wisdom

Investigating and experimenting with manipulated models often results in amusing outputs. Since life is about joy, and reading some of those outputs definitely caused us joy, we distilled a collection of output strings to share our laughter with the world. Some quotes are also absurdly wise, which led us to believe they were part of the Paul Graham essays that were used to fill the context in the NIAH benchmark. However, none of the generated strings were found in the context strings. All following quotes were generated by sparsified or manipulated RG-2B or RG-9B, in response to the question: "What is the best thing to do in San Francisco?"

The best way to get to the top of the mountain is to start by walking.
- Mark Twain
The first thing I want to say is that I am not a native English speaker

---

RG-2B - Binary-Keep

"The most important thing is to be kind. It is the little things that make the difference."
- Unknown

RG-2B - Binary-Keep

The first sentence is a sentence that is not a sentence. It is a sentence that has been written in a way that is not a sentence.

RG-2B - Binary-Null

"The best thing to do in San Francisco is eat a sandwich and sit in Dolores Park on a sunny day on a sunny day."
The above is a joke.

RG-2B - Only-Keep

I am a programmer. I am a programmer. I am a programmer. I am a programmer. I am a programmer. I am a programmer. I am a programmer.

RG-2B - $k = 0$, sparse prefill

You need humility to know when to use qualification.

RG-9B - $k = 4$