Hybrid Architectures for Language Models: Systematic Analysis and Design Insights

Sangmin Bae 1,3,* , Bilge Acun 1 , Haroun Habeeb 2 , Seungyeon Kim 2 , Chien-Yu Lin 1 , Liang Luo 2 , Junjie Wang 2 , Carole-Jean Wu 1

¹FAIR at Meta, ²Meta, ³KAIST AI

Recent progress in large language models demonstrates that hybrid architectures—combining self-attention mechanisms with structured state space models like Mamba—can achieve a compelling balance between modeling quality and computational efficiency, particularly for long-context tasks. While these hybrid models show promising performance, systematic comparisons of hybridization strategies and analyses on the key factors behind their effectiveness have not been clearly shared to the community. In this work, we present a holistic evaluation of hybrid architectures based on inter-layer (sequential) or intra-layer (parallel) fusion. We evaluate these designs from a variety of perspectives: language modeling performance, long-context capabilities, scaling analysis, and training and inference efficiency. By investigating the core characteristics of their computational primitive, we identify the most critical elements for each hybridization strategy and further propose optimal design recipes for both hybrid models. Our comprehensive analysis provides practical guidance and valuable insights for developing hybrid language models, facilitating the optimization of architectural configurations.

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Correspondence: bsmn0223@kaist.ac.kr, carolejeanwu@meta.com

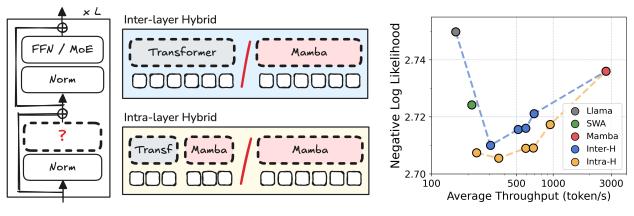
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1 Introduction

Recent language models (Llama Team, 2024; Microsoft Research, 2024; DeepSeek-AI, 2024; OpenaAI et al., 2024; Qwen Team, 2025; Gemini Team, 2025) have demonstrated strong scalability and human-like performance across a wide range of tasks. Most of these models are based on the Transformer architecture (Vaswani et al., 2017), which alternates self-attention and feed-forward layers. However, the self-attention mechanism exhibits quadratic complexity with respect to input sequence length, leading to slow inference and a substantial memory footprint. To address these limitations, a new class of computational primitives—state space models (SSMs)—has emerged, inspired by signal processing (Gu et al., 2020, 2021a,b, 2022; Fu et al., 2022; Gu and Dao, 2023; Dao and Gu, 2024; Yang et al., 2024). These architectures scale more efficiently to long sequences by compressing prior context into a finite-dimensional state. Among these, the Mamba model (Gu and Dao, 2023; Dao and Gu, 2024) stands out for being competitive with Transformer on language modeling, while also accelerating training speed through work-efficient parallel scan algorithms (Blelloch, 1990; Smith et al., 2022).

These new primitives expand the architecture design space, opening up new possibilities for hybrid models that leverage the strengths of different architectural choices (Glorioso et al., 2024b; Ren et al., 2024; Lieber et al., 2024; Wang et al., 2024a; Poli et al., 2024; Dong et al., 2024; Ren et al., 2025; Basant et al., 2025). Notably, mixing Transformer and Mamba blocks often outperforms homogeneous architectures, while maintaining high efficiency. Most prior work on hybrid models has focused on the sequential interleaving of standard Transformer and Mamba blocks—an *inter*-layer hybrid approach (Glorioso et al., 2024b; Ren et al., 2024; Jamba Team et al., 2024; Hunyuan Team et al., 2025). This practical strategy allows for a balance between model quality and throughput by adjusting the ratio of quadratic (Transformer) to linear (Mamba) attention blocks. In addition, a few *intra*-layer hybrid models have been proposed, which fuse the two primitives in parallel within individual layers. These approaches use either head-wise (Dong et al., 2024; Xiao et al., 2025) or sequence-wise splits (Zhang et al., 2024; Li et al., 2025b) to further combine the benefits of both architectures at a finer granularity. Figure 1a summarizes which attention primitives each hybridization type can use.

^{*}Work done at Meta



(a) Overview of hybrid architecture

(b) Pareto frontier of throughput

Figure 1 (a) Two hybridization strategies construct attention using either Transformer (or intra-hybrid) or Mamba blocks. Varying ratios of these blocks controls the degree of hybridization. In intra-hybrid blocks, all heads are split into two halves, which are then processed by half-sized Transformer and Mamba blocks, respectively. (b) The hybrid architectures achieve superior quality-throughput trade-offs compared to homogeneous architectures. Negative log likelihood (i.e., loss) is measured on the DCLM validation set, and inference throughput is averaged across total lengths of 2K, 4K, 8K, 16K, and 32K, with the prompt length fixed at 512. All models have 1B parameters and are trained with the same FLOPs budget of 4.5e20 and 8K context length. For hybrids, we connect results for different block ratios (1:0, 1:1, 1:3, 1:5, 1:12, 0:1)—where each ratio denotes (Transformer / Intra-hhybrid: Mamba blocks)—with dashed lines. In the sliding window attention (SWA) model, global attention and SWA are interleaved at a 1:5 ratio, with a window size of 512 and an attention sink size of 64 (Gemma Team et al., 2025; Cohere et al., 2025; OpenAI et al., 2025).

Despite the emergence of various hybrid architectures, the current literature lacks openly shared, in-depth analysis of hybridization strategies, making it difficult to understand their relative strengths and design trade-offs (Sun et al., 2025). In particular, most prior works focus on introducing specific hybrid architectures rather than providing detailed, systematic comparisons across possible hybridization approaches. As a result, the key intuitions driving final design choices, as well as the relative merits of different strategies from multiple perspectives, remain open questions for the community.

In this work, we address these research questions by conducting a holistic evaluation of hybrid architectures via comprehensive, multi-faceted comparisons. Specifically, for model architecture choices, we compare inter-layer and intra-layer hybridization strategies with Transformer (Llama Team, 2024), Mamba (Dao and Gu, 2024), and striped models of global and sliding window attention (Beltagy et al., 2020; Gemma Team et al., 2025) with attention sink (Xiao et al., 2023). From quality perspectives, we identify optimal design choices for hybrid models by providing key insights into critical architectural considerations, based on language modeling perplexity (§4.1) and extensive ablation studies (§4.5 and §4.6). Additionally, we analyze long-context retrieval performance (Rae et al., 2019a; Kamradt, 2023) with the characteristics of each computational primitive (§4.3). Our exploration of Mixture-of-Experts (Fedus et al., 2022; DeepSeek-AI, 2024) and compute-optimal scaling (Kaplan et al., 2020; Hoffmann et al., 2022) further offers practical guidance for scaling up hybrid models (§4.4). On the efficiency front, we conduct an in-depth comparison of both training and inference, measuring training time, memory usage, inference throughput, and cache size (§4.2). Based on our comprehensive experiments, we summarize the principal insights regarding hybrid architectures as follows:

[Quality] Both hybrid model types outperform homogeneous architectures up to 2.9% accuracy and even surpass widely adopted SWA models in quality. Intra-layer hybridization shows best pareto-frontier of model quality and efficiency (see Figure 1b and Table 2).

[Quality] While baselines show poor in-context retrieval and length generalization, all hybrid architectures achieve robust and superior long-context retrieval (see Figures 3c and 4).

[Quality] Hybrid models are fully compatible with MoE structures and achieve an optimal compute-scaling slope between those of Transformer and Mamba (see Table 3).

	Compute	Memory							
Models	FLOPs per Sample	Parameter Counts	Cache Size						
Llama	$12d_{\text{model}}L_{\text{ctx}}\times(L_{\text{ctx}}+1)/2$	$2d_{\mathrm{model}}d_{\mathrm{model}} + 2d_{\mathrm{model}}d_{\mathrm{head}}N_{kv}$	$\begin{vmatrix} 2d_{\text{head}}N_{kv}L_{\text{ctx}} \\ +2d_{\text{head}}N_{kv}L_{\text{ctx}} \end{vmatrix}$						
Sliding Window	$ \begin{vmatrix} 12d_{\text{model}}L_{\text{swa}} \\ \times ((L_{\text{swa}}+1)/2 + (L_{\text{ctx}}-L_{\text{swa}})) \end{vmatrix} $	$ \begin{vmatrix} 2d_{\text{model}}d_{\text{model}} \\ +2d_{\text{model}}d_{\text{head}}N_{kv} \end{vmatrix} $	$ \begin{array}{c c} 2d_{\text{head}}N_{kv}L_{\text{swa}} \\ +2d_{\text{head}}N_{kv}L_{\text{swa}} \end{array} $						
Mamba		$\begin{vmatrix} d_{\text{model}}(2d_{\text{ssm}} + 2d_{\text{state}} + N_{\text{head}}) \\ + d_{\text{state}}(N_{\text{conv}} + d_{\text{model}}) + 2N_{\text{head}} \end{vmatrix}$	$ \begin{vmatrix} 2d_{\text{ssm}}d_{\text{state}} \\ +2N_{\text{conv}}(2d_{\text{state}} + d_{\text{ssm}}) \end{vmatrix} $						

Table 1 Overall comparison of per-block compute and memory costs across different primitives. For simplicity, we exclude the additional term of 6 times the block parameter count from FLOPs. Here, N denotes number, d is dimension, and L is sequence length. L_{swa} is the sum of sliding window size and attention sink sizes, and d_{ssm} is typically $2d_{\text{model}}$. For Transformers, we assume grouped-query attention, and cache sizes are calculated with bfloat16 precision.

[Efficiency] By fully leveraging Mamba's efficiency strengths (i.e., linear complexity with respect to sequences), hybrid models achieve fast end-to-end training time (see Figure 2) and high inference throughput with lower cache sizes (see Figures 1b, 3a, and 3b).

[Design] Insights about optimal block ratios, ordering of computational primitives for hybrid architectural configurations are thoroughly explored (see Tables 4 and 5).

2 Background

Transformer architecture. The Transformer architecture (Vaswani et al., 2017) consists of two main components: the multi-head attention (MHA) module and a feed-forward network (FFN). The MHA mechanism leverages multiple attention heads to capture diverse dependencies within the input sequence. For each head, attention is computed as follows:

$$\operatorname{Attention}(\mathbf{Q}, \mathbf{K}, \mathbf{V}) = \operatorname{softmax}\left(\frac{\mathbf{Q}\mathbf{K}^T}{\sqrt{d_k}}\right)\mathbf{V},$$

where \mathbf{Q} , \mathbf{K} , and \mathbf{V} are derived from learned linear projections of the input using \mathbf{W}_{ℓ}^Q , \mathbf{W}_{ℓ}^K , and \mathbf{W}_{ℓ}^V , respectively. The outputs of all heads are concatenated and transformed by \mathbf{W}_{ℓ}^O to restore the original model dimension. To reduce key-value cache size, recent models divide query heads into groups, with each group sharing a single key and value head—a structure known as grouped-query or multi-query attention (Ainslie et al., 2023). On the other hand, sliding window attention (SWA) (Beltagy et al., 2020; Jiang et al., 2023) reduces the context length over which queries attend to key and value states. For the FFN component, recent models adopt a gating structure based on the SiGLU mechanism, which is a variant of SwiGLU (Shazeer, 2020; Chowdhery et al., 2023) but uses the SiLU activation instead of Swish. This FFN can be replaced with a Mixture-of-Experts layer (Shazeer et al., 2017; Fedus et al., 2022), where multiple FFNs (experts) are adaptively routed for each token.

Mamba architecture. The Mamba architecture (Gu and Dao, 2023) is a recent advancement in sequence modeling, building on structured state space models like S4 (Gu et al., 2021a), H3 (Fu et al., 2022), and S4D (Gu et al., 2022). Mamba replaces the attention mechanism with a state space model (SSM) layer, enabling efficient and expressive modeling of long-range dependencies:

$$\mathbf{h}_t = \bar{\mathbf{A}}\mathbf{h}_{t-1} + \bar{\mathbf{B}}\mathbf{x}_t, \quad \mathbf{y}_t = \mathbf{C}\mathbf{h}_t + \mathbf{D}\mathbf{x}_t$$

Here, \mathbf{h}_t represents the latent state at time t, \mathbf{x}_t is the input, and \mathbf{y}_t is the output. In practice, $\bar{\mathbf{A}}$ is discretized using zero-order hold (ZOH), and $\bar{\mathbf{B}}$ is discretized via the Euler method. A key innovation is the input-dependent modulation of the state space parameters \mathbf{B} , \mathbf{C} , and the discretization step Δ , allowing the model to flexibly control context retention and input integration for each token. This selectivity enables Mamba to match

the modeling quality of Transformers. Additionally, inspired by gated attention units (Hua et al., 2022), Mamba incorporates a SiLU-based gating mechanism. Mamba 2 (Dao and Gu, 2024) advances this design by introducing the state space duality (SSD) layer, which reformulates SSM computations as matrix multiplications highly optimized for modern hardware (e.g., GPUs, TPUs). This results in significantly faster training and improved practical efficiency. Throughout this paper, we primarily utilize the Mamba 2 architecture as the computational primitive, with each block always followed by a FFN layer, which can optionally be replaced with a MoE layer.

Computate and memory costs comparison. When analyzing costs in hybrid architectures (also for SWA models combining global and local attention), we reference the per-block costs in Table 1 (see Appendix C for details). For example, in a 1B model with 8K context, Transformer uses about 18% more FLOPs per sample than Mamba, due to its quadratic scaling versus Mamba's linear scaling. From a memory perspective, Mamba uses $2.5 \times$ more parameters per block (25M vs. 10M), but its cache size is 95% smaller than that of a Transformer (256 MiB vs. 13.4 MiB).

3 Hybrid Architecture

Hybrid architectures can be categorized by their integration approach: inter-layer and intra-layer hybridization. We define each strategy and outline related research questions below.

3.1 Inter-layer Hybrid Model

Definition. The inter-layer hybrid model alternates softmax attention layers with linear sequence modeling layers at specific intervals (see Figure 1a). A key design choice in this approach is determining the order and proportion in which Transformer and Mamba primitives are arranged and interpolated. Its practical effectiveness and straightforward implementation have made the inter-layer approach a dominant strategy in hybrid architecture development.

Related works. Most recent hybrid models combine Mamba (Gu and Dao, 2023; Dao and Gu, 2024) with various attention mechanisms to enhance quality and efficiency. Notable examples—Zamba (Glorioso et al., 2024b,a), Jamba (Jamba Team et al., 2024; Lieber et al., 2024), Samba (Ren et al., 2024, 2025), Hunyuan-TurboS (Hunyuan Team et al., 2025), Nemotron nano 2 (Basant et al., 2025), and IBM Granite 4.0—share similar designs that leverage Mamba's efficiency with global or local attention, scaling to over 1M context length. Some post-training approaches—such as MambaInLLaMA (Wang et al., 2024a), MOHAWK (Bick et al., 2024), Zebra-Llama (Yang et al., 2025), and Jet-Nemotron (Gu et al., 2025)—use knowledge distillation to convert parts of a pretrained Transformer into linear modules, while STAR (Thomas et al., 2024) and Composer (Acum et al., 2025) perform architecture search from scratch. Other hybrids—RecurrentGemma (Botev et al., 2024), Griffin (De et al., 2024), Titans (Behrouz et al., 2024), RWKV-X (Hou et al., 2025), MiniMax-01 (Li et al., 2025a), and Qwen3-Next—combine diverse self-attention variants (Beltagy et al., 2020; Qin et al., 2024; Lu et al., 2025; Qiu et al., 2025) with different linear modules (Qin et al., 2022; De et al., 2024; Yang et al., 2024; Peng et al., 2025).

Block ratios in inter-layer hybrid. One of the key research questions in designing inter-layer hybrids is determining the optimal ratio of Transformer blocks to Mamba blocks when stacking layers. This ratio determines the degree of interpolation between two computational primitives, impacting not only model quality but also efficiency metrics like throughput and cache size. Prior work (Jamba Team et al., 2024; Lieber et al., 2024; Basant et al., 2025) has generally favored configurations with a high proportion of Mamba layers—for example, a 1:7 ratio. We revisit this design choice and offer deeper insights by comparing various ratios from both quality and efficiency perspectives.

Positioning of computational primitives. Another open question is whether the position of interleaved blocks affects model quality, and how best to arrange them for optimal performance. There is currently no clear consensus on optimal positioning, as it may depend on factors such as block ratio and model scale. Although prior work (Lieber et al., 2024; Ren et al., 2025; Basant et al., 2025) often places Transformer blocks in the middle layers, comprehensive studies on this topic are still lacking. To fill this gap, we conduct extensive ablation experiments, varying the positions of Transformer blocks (e.g., early, middle, and late layers) across different ratios and model sizes.

3.2 Intra-layer Hybrid Model

Definition. Intra-layer hybrid models achieve fine-grained fusion within individual layers by blending softmax attention and linear attention in parallel. A common approach (Dong et al., 2024; Xiao et al., 2025) is head-wise splitting, where some heads use Transformer attention while others use Mamba (see intra-hybrid block in Figure 1a). Here, we use intra-hybrid and Mamba blocks as primitive candidates, so that this includes an interleaving mechanism akin to inter-layer hybrid models.

Related works. Intra-layer hybrid models can be classified by how each token interacts with different modules. In the head-wise splitting approach (e.g., Hymba (Dong et al., 2024), WuNeng (Xiao et al., 2025)), attention heads are divided into groups, with each group assigned to a distinct module. Alternatively, works like Liger (Lan et al., 2025) process each token through all modules in parallel and fuse the outputs. For sequence-wise splitting, different modules are applied to context tokens based on their positions when computing attention scores. This splitting can be determined by an absolute point in the sequence, as in TransMamba (Li et al., 2025b), or by relative position, as in LoLCATs (Zhang et al., 2024). While not hybrid, differential architectures such as Diff-Transformer (Ye et al., 2024) and Diff-Mamba (Schneider et al., 2025) also use head-wise splitting, but use the same primitive type and subtract their attention scores.

Architectural variants for intra-layer hybrid. We adapt a head-wise splitting approach, assigning different primitives to two groups of attention heads. Especially, query and key states in Transformer are projected to reduced dimensions, while the value state is expanded back to the original size (Ye et al., 2024; Schneider et al., 2025). For Mamba, the hidden dimension of SSMs is similarly reduced based on configuration. Various fusion designs are explored, including normalization strategies—with or without group normalization (Wu and He, 2018) as in Hymba (Dong et al., 2024)); learnable scalar—such as scaling (Dong et al., 2024; Ye et al., 2024; Schneider et al., 2025) or gating parameters (Lan et al., 2025; Xiao et al., 2025); fusion operations—including addition (Dong et al., 2024; Lan et al., 2025; Xiao et al., 2025), subtraction (Ye et al., 2024; Schneider et al., 2025), or concatenation (Xiao et al., 2025); and the number of output projection. We thoroughly evaluate these variants at both 350M and 1B scales, comparing their performance to existing intra-hybrid architectures.

Dimension ratios in intra-hybrid block. The ratio of parameter sizes between Transformer and Mamba modules within intra-hybrid blocks—controlled by their hidden dimension allocations—is one of key architectural considerations. By observing how model quality changes as this ratio varies, we can infer the relative importance of each primitive. Furthermore, assuming expert parallelism (Rajbhandari et al., 2022) enables parallel execution of the modules, overall efficiency will be bounded by the slower Transformer component. Thus, we investigate how much we can reduce the dimension assigned to the Transformer, aiming to enhance efficiency without compromising overall quality.

Block ratios and positioning of primitives. In our intra-layer hybrid, each block is either an intra-hybrid block or a Mamba block. By varying the block ratio to control the interpolation degree, we analyze how different configurations affect both quality and efficiency, aiming to understand the trade-offs in intra-hybridization. We further examine how the placement of these intra-hybrid blocks at different depths influences model quality. Since both Transformer and Mamba are included, unlike using homogeneous primitives, we explore how its behavior differs from that of inter-layer hybrid models.

4 Experiments

We build hybrid models with computational primitives following the configurations of Llama 3.2 (Llama Team, 2024) and Mamba 2 (Dao and Gu, 2024) architectures. We use the TorchTitan framework (Liang et al., 2024) for large-scale LLM training with H200 GPUs. See Appendix D for further details.

4.1 Main Results on Quality

Hybrid architectures significantly outperform homogeneous models. Table 2 compares our two hybridization strategies—optimized along positioning and design choice axes (see §4.5 and §4.6)—with conventional baselines (Llama Team, 2024; Dao and Gu, 2024; Gemma Team et al., 2025). Our controlled experiments show that hybrid models, including SWA, consistently outperform homogeneous models in negative log-likelihood (NLL)

	Base Config				Compute			NLL (↓)		Few-shot Accuracy (†)						
Models	N-emb	$N_{ m attn}$	$N_{ m swa}$	$N_{ m ssm}$	$N_{ m mix}$	Tok	FLOPs	Cache	DCLM	PG19	LD	HS	PQ	ARC	ОВ	Avg
Llama	0.97B	16	-	-	-	60B	$4.5\mathrm{e}20$	256	2.750	2.875	56.1	55.2	72.8	43.2	32.7	52.0
SWA	0.97B	3	13	-	-	60B	$3.8\mathrm{e}20$	63	2.741	2.867	56.0	55.9	72.6	44.2	34.8	52.7
Mamba	0.99B	-	-	13	-	60B	$3.7\mathrm{e}20$	13	2.758	2.891	53.7	55.1	73.8	43.9	35.2	52.3
Inter-H	0.96B	2	-	11	-	60B	$3.7\mathrm{e}20$	43	2.735	2.861	56.4	55.4	73.1	44.8	36.6	53.3
Intra-H	0.98B	-	-	11	2	60B	$3.7\mathrm{e}20$	38	2.728	2.853	58.7	57.4	73.3	47.9	36.4	54.7
SWA	0.97B	3	13	-	-	71B	$4.5\mathrm{e}20$	63	2.724	2.845	57.0	56.9	73.1	46.0	36.0	53.8
Mamba	0.97B	-	-	13	-	73B	$4.5\mathrm{e}20$	13	2.736	2.865	55.2	57.1	73.8	45.3	36.0	53.5
Inter-H	0.96B	2	-	11	-	73B	$4.5\mathrm{e}20$	43	2.716	2.842	56.7	57.6	73.3	46.5	35.8	54.0
Intra-H	0.98B	-	-	11	2	72B	$4.5\mathrm{e}20$	38	2.709	2.831	58.4	57.7	74.4	46.9	37.0	54.9

Table 2 Hybrid models achieve better quality than baselines under equal data and compute constraints. $N_{\rm mix}$ denotes the number of intra-hybrid block primitive. We calculate total training compute FLOPs and cache sizes for a sequence length of 8K tokens. We use an approximate block ratio of 1:5 for SWA and hybrid architectures, which mix two different types of block.

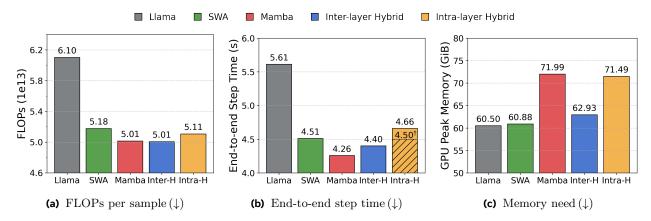


Figure 2 Hybrid models have lower FLOPs, which directly leads to reduced actual training time. We measure metrics for 1B model using 8 H200 GPUs with FSDP, torch.compile, 8K lengths, and a local batch size of 4, without activation checkpointing. Both SWA and hybrid models use a 1:5 block ratio. † indicates a theoretical time achievable with parallelism (Rajbhandari et al., 2022).

and few-shot accuracy under the same data budget. This demonstrates that effectively combining complementary inductive biases from different primitives is key to improving model quality through hybridization. Notably, we provide a meaningful comparison between inter- and intra-hybrid architectures under matched budgets, which has not been previously explored or shared (Ren et al., 2024; Jamba Team et al., 2024; Dong et al., 2024; Basant et al., 2025). Under the same FLOP budget, hybrids achieve even more substantial quality gains (e.g., 2.9% increase in accuracy and 0.04 reduction in NLL). We find that these advantages are consistent across different block ratios and model scales, demonstrating the robustness of the hybrid approach (see Figure 1b).

4.2 Main Results on Efficiency

FLOPs reduction in hybrid models translate into faster actual end-to-end training time. Mamba's linear complexity leads to lower FLOPs than Transformer (18% lower for 1B scale at 8K lengths; see Table 1 for details). As shown in Figure 2, hybrid models leverage these advantage for superior performance in compute-bound scenarios. Empirically, lower FLOPs almost directly yield faster training, aided by parallel scan algorithms (Blelloch, 1990; Smith et al., 2022). For intra-hybrid models, the expert parallelism (Rajbhandari et al., 2022) can theoretically optimize training speed further. Although Mamba and hybrid models may use slightly more memory during training, adjusting the block ratio provides flexibility to balance between efficiency and model quality.

Hybrid models achieve a superior Pareto frontier of inference throughput and quality. Figures 3a and 3b demonstrate that hybrid architectures, by leveraging Mamba's linear complexity and constant cache size, sustain

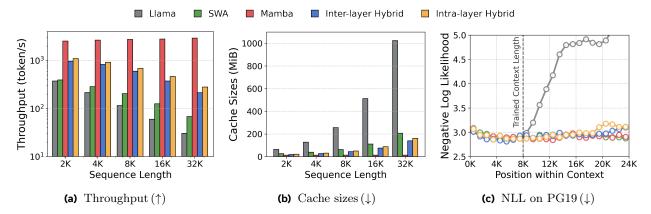


Figure 3 (a, b) Hybrid architectures show sub-quadratic scaling of inference throughput and memory as sequence increases. SWA and hybrid 1B models use block ratio of 1:5. For throughput, we set the prompt length to 512 and the batch size to 4. (c) Mamba enables length generalization in terms of perplexity, allowing hybrids to maintain strong performance. We use 1B models trained with a compute budget of 4.5e20 and 8K lengths. Loss is averaged every 1K positions over 30 samples.

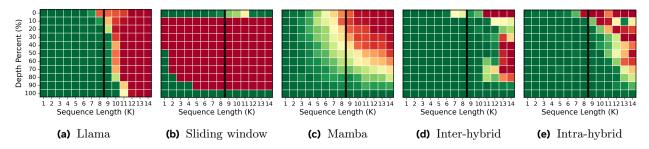


Figure 4 Hybrid models overcome the limitations of both foundational primitives, achieving superior in-context retrieval performance. We insert a needle (random 7-digit number associated with random city name (Gemini Team et al., 2024)) across the 0–100% depth range (y-axis) for context lengths up to 14K (x-axis). Over 100 trials, green indicates 100% accuracy, while red denotes 0% accuracy. We use 1B model checkpoints trained with 8K length and a FLOPs budget of 4.5e20. SWA and hybrid models use 1:5 block ratio.

high throughput and sub-quadratic memory growth across context lengths. This enables faster generation compared to baselines, while still maintaining high output quality (see Figure 1b). Although SWA uses a 512+64 (window $+\sin k$) attention map, it remains slower than Mamba's linear attention, making hybrids overall faster. Interestingly, intra-layer hybrids, which utilize half-sized Transformer, further outperform inter-layer hybrids even when executed sequentially.

4.3 Long-context Capability Evaluation

Position-wise loss on PG19 shows hybrid-Mamba models extrapolates well to longer contexts. Figure 3c compares position-wise loss on the PG19 corpus (Rae et al., 2019a) to examine the long-context capabilities of various architectures. All models show decreasing NLL up to the 8K-token pretraining context, as later tokens benefit from more context. Beyond 8K, SSMs can effectively extrapolate (Gu and Dao, 2023; Dao and Gu, 2024; Yang et al., 2024), while Transformer struggles due to its positional encoding methods (Press et al., 2021; Kazemnejad et al., 2023; Zhou et al., 2024). Therefore, both hybrid architectures with a 1:5 block ratio benefit more from Mamba, demonstrating stronger length generalization. This characteristic will vary depending on the interpolation degree determined by the block ratio.

Hybrid models overcome weakness of Transformer and Mamba in in-context retrieval. Figure 4 presents in-context retrieval performance on the Needle-In-A-Haystack benchmark (Kamradt, 2023; Kuratov et al., 2024). A needle is inserted at a specific depth in the context, and models are evaluated on their ability to retrieve (generate) it. Transformer accuracy drops to near zero beyond 8K context length, as expected. On the other

			Base (Config		Мо	E	Performance (\psi / \psi / \equiv)			
Models	Act	Total	$N_{ m attn}$	$N_{ m ssm}$	$N_{ m mix}$	FLOPs	Num	Act	$\overline{\text{DCLM}}$	PG19	Acc
Llama	0.97B 0.97B	0.97B 3.79B	16 16	-	-	$\begin{array}{c} 4.5e20 \\ 4.5e20 \end{array}$	- 1+8	- 1+1	2.750 2.656	2.875 2.775	52.0 55.8
Mamba	0.99B 0.99B	0.99B 3.28B	-	13 13	-	3.7 e20 3.7 e20	- 1+8	- 1+1	2.758 2.673	2.891 2.803	52.3 55.0
Inter-H	0.96B 0.96B	0.96B 3.25B	2 2	11 11	-	3.7 e20 3.7 e20	- 1+8	- 1+1	2.735 2.653	2.861 2.780	53.3 56.0
Intra-H	0.98B 0.98B	0.98B 3.27B	- -	11 11	2 2	3.7 e20 3.7 e20	- 1+8	- 1+1	2.728 2.648	2.853 2.775	54.7 56.9

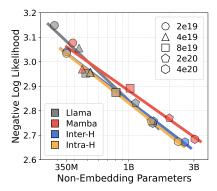


Table 3 (Left) All architectures consistently achieve significant quality gains from MoE integration. All models are trained on 60B tokens, with hybrid models using a 1:5 block ratio. We use one shared expert and the selected top-1 expert among eight. Additionally, a token-choice router with loss-free balancing algorithm is utilized (Wang et al., 2024b; DeepSeek-AI, 2024). (Right) Hybrid architectures demonstrates a compute-optimal scaling line that lies between those of Transformer and Mamba. We train models at four different scales—100M, 350M, 1B, and 3B—across five compute budgets. Each marker indicates the optimal model size for a given compute budget. For hybrid models, we use a 1:5 block ratio.

hand, SWA and Mamba also struggle with retrieval outside their local window and sink token regions, or in long-range tokens, despite strong perplexity scores in Figure 3c; this is likely due to their focus on local information (Ben-Kish et al., 2024). In contrast, both inter- and intra-hybrid models surprisingly maintain strong retrieval performance up to about 1.5x the pretraining length, overcoming the limitations of the base primitives rather than simply inheriting them. While retrieval accuracy in the middle of extrapolated contexts does decline (Liu et al., 2023), hybrid models consistently demonstrate improved retrieval capabilities.

4.4 Scaling Analysis

Mixture-of-Experts are fully compatible with hybrid architectures. A few recent inter-layer hybrid models (Lieber et al., 2024; Jamba Team et al., 2024) have incorporated Mixture-of-Experts (MoE) (Shazeer et al., 2017; Fedus et al., 2022) to improve performance at fixed compute. In Table 3, we re-examine MoE in inter-layer hybrids and also evaluate intra-layer hybridization, comparing both to baseline models. Across all architectures, MoE yields a substantial reduction in NLL (by 0.08) and 4 point increase in few-shot accuracy. Since hybridization is applied to the attention component, integrating MoE into the FFN layer remains compatible with all hybrid models. The data-hungry nature of MoE also enables more efficient scaling of hybrid models for a fixed number of activated parameters.

Hybrid models are efficient and scalable architectures. The figure to the right of Table 3 analyzes the scalability of different model architectures and identifies compute-optimal scaling strategies (Kaplan et al., 2020; Hoffmann et al., 2022). The compute-optimal line illustrates the best achievable quality and parameter sizes for each architecture under a given computational budget. Mamba performs best with larger models and less data feeding, while Transformers favor a higher token-to-parameter ratio of around 20 (Hoffmann et al., 2022). Hybrid models show intermediate scaling behavior, with intra-layer hybrids being a little slightly more data-hungry. These results provide clear guidance on how to optimally scale up hybrid architectures.

4.5 Ablation Studies for Inter-layer Hybridization

To ensure quality, aim for a high 1:1 ratio, but to balance with efficiency, use about 1:5 ratio. In Table 4, we compare inter-hybrid models with six block ratios at two scales (1:0 = Transformer, 0:1 = Mamba). Hybrid architectures consistently outperform homogeneous ones, with the balanced 1:1 ratio yielding the best quality. However, due to the Transformer's quadratic complexity, inference throughput gains become limited. To balance both efficiency and quality, a ratio of around 1:5 appears to be optimal, which aligns with the lower ratios (e.g., 1:5, 1:7) adopted by large hybrid language models (Lieber et al., 2024; Wang et al., 2025; Basant et al., 2025).

		Ba	se Config	5	Performance (↓ / ↓ / ↑)					
Sizes	Ratio	N-emb	$N_{ m attn}$	$N_{ m ssm}$	DCLM	PG19	Acc			
	1:0	0.97B	16	-	2.750	2.875	52.0			
	0:1	0.99B	-	13	2.758	2.891	52.3			
1D	1:1	0.96B	7	7	2.725	2.847	54.0			
1B	1:3	0.94B	3	10	2.732	2.857	53.8			
	1:5	0.96B	2	11	2.735	2.861	53.3			
	2.866	53.1								
	1:0	0.35B	14	-	2.882	3.015	48.7			
	0:1	0.35B	-	11	2.880	3.024	48.7			
350M	1:1	0.35B	6	6	2.850	2.985	49.3			
OOUM	1:3	0.34B	3	8	2.858	2.994	50.2			
	1:5	0.35B	2	9	2.860	2.999	49.4			
	1:12	0.36B	1	10	2.864	3.003	49.3			



Table 4 (Left) Inter-layer hybrid achieves the best quality at a 1:1 block ratio, but the 1:5 ratio is preferable to balance efficiency and quality. Transformer blocks are evenly distributed in the middle. All models are trained on 60B tokens. (Right) Interleaving Transformer blocks at intermediate depths is key for optimal performance. The upper figure shows results of ablating the position of a single Transformer block in 1B (13 layers) and 350M (11 layers) models with a 1:12 ratio. In the lower figure, after distributing Transformer blocks in the middle of 1B model, we move the first block to the first layer (Front) or the last block to the last layer (End). All models are trained on 60B tokens.

Never place Transformer blocks at the front. Deciding the order of Transformer and Mamba blocks is a key design choice. Our ablation study (see figures next to Table 4) shows that, for a 1:12 ratio, placing the Transformer block in the early layers leads to significant performance drop, while positioning it in the middle yields the best results. Similar experiments with higher block ratios (bottom-right figure) also confirm that putting Transformer blocks at the front consistently leads to worse performance than homogeneous models, regardless of ratio. These finding support prior work favoring middle placement of Transformer (Jamba Team et al., 2024; Dong et al., 2024). In the future, more efficient methods like layer-wise sensitivity analysis (Yang et al., 2025) or architecture search (Thomas et al., 2024) may help optimize block positions.

4.6 Ablation Studies for Intra-layer Hybridization

Novel outperforming architectural variant for intra-hybrid block. In designing intra-hybrid blocks, we explore four axes: normalization layer, learnable scalar, fusion operation, and output projection. In Table 5, our experiments reveal that normalization is crucial due to the scale differences between modules (Dong et al., 2024), which makes additional scaling factors unnecessary. For output fusion, either subtracting the outputs to mitigate attention noise or simply concatenating them yield the best quality. The resulting architecture surpasses previous intrahybrid models (Dong et al., 2024), and hybridizing Transformer and Mamba proves superior in both quality and efficiency over differential architectures that use same type of primitives (Ye et al., 2024; Schneider et al., 2025).

Enlarging Transformer dimension improves quality, despite reduced efficiency. The upper-right figure presents ablation results for dimension allocation ratios within the intra-hybrid block, defined by the proportion of query / key dimension in Transformer versus pre-expansion dimension in Mamba (with 1:0 and 0:1 representing pure Transformer and Mamba, respectively). The results indicate that a balanced allocation is important for quality, with larger Transformer dimensions leading to greater performance gains—suggesting that the Transformer component even plays a more critical role than Mamba. However, since throughput is limited by the Transformer under parallel execution, a 1:1 dimension ratio offers a practical and effective balance.

Evenly scattering intra-hybrid blocks across depths yields the best quality. We further investigate block ratio and ordering strategies for intra-hybrid models (see lower figure next to Table 5). Increasing the proportion of Transformer-containing intra-hybrid blocks consistently improves quality, in line with previous findings on primitive importance from dimension ratio ablations. However, using more Mamba blocks remains a practical choice for efficiency. For block positioning, motivated by lessons from §4.5, we keep intra-hybrid blocks in the middle positions for ablation studies. Notably, evenly distributing these intra-hybrid blocks across depths yields the best results, while placing them at the ends (Sandwich strategy) leads to huge performance drops.

		Desi	Performance (↓ / ↓ / ↑)					
Models	Module	Norm	Scalar	Fusion	Out	DCLM	PG19	Acc
Llama	Т	-	-	-	1	2.750	2.875	52.0
Mamba	M	-	-	-	1	2.758	2.891	52.3
Diff-T	T/T	-	Diff-T	Diff	1	2.727	2.848	53.6
Diff-M	M/M	-	Diff-M	Diff	2	2.759	2.892	53.0
Hymba	T/M	Group	Scale	Add	1	2.726	2.846	52.4
	T/M	-	Scale	Add	1	2.740	2.865	53.9
	T/M	Group	-	Add	1	2.721	2.840	54.5
	T/M	Group	Gate	Add	1	2.751	2.876	53.1
Variants	T / M	Group	-	Diff	1	2.721	2.842	54.0
	T/M	Group	-	Conc	1	2.715	2.833	54.8
	T/M	Group	-	Add	2	2.714	2.834	54.5
	T/M	Group	-	Diff	2	2.712	2.831	54.9

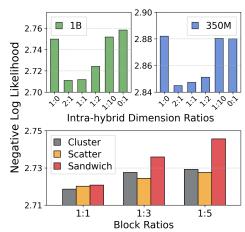


Table 5 (Left) We identify a more optimal architecture than previous designs through ablation studies on intra-hybrid block. We train a 1B model on 60B tokens, replacing all layers with intra-hybrid blocks (i.e., 1:0 block ratio). All heads are split into two, with each linked to a half-sized primitive. (Right) Keeping larger Transformer dimension within intra-hybrid block improves quality (despite reduced efficiency), and placing the intra-hybrid block in the middle yields the best results. All 1B models with the optimal architecture from left, are trained on 60B tokens. In the figure above, we use a block ratio of 1:0, where all layers become intra-hybrid blocks. For lower figure, we place intra-hybrid blocks in the middle of 1B model by: placing consecutively (Cluster), distributing evenly (Scatter), or placing at the beginning and end as well (Sandwich).

5 Conclusion and Future Work

In this work, we present a holistic analysis for inter-layer and intra-layer hybrid architectures. Our comprehensive evaluation demonstrates that hybrid models consistently outperform homogeneous architectures across multiple quality metrics, with intra-layer hybrids showing the strongest results. Notably, these hybrid approaches also deliver superior efficiency, achieving faster training and inference, much more than widely adopted sliding window attention models. Our findings shed new insights and practical guidance for designing high-quality, efficient hybrid architectures.

Validation at scale. Our study is limited to 1B models, pretrained on 60B tokens. Since standalone Mamba models often show diminishing returns at scale (Waleffe et al., 2024), a crucial next step is to validate whether the performance advantages of our hybrid model persist with longer training and at larger scales. However, we are optimistic they will, based on our scaling analysis up to the 3B parameter size and prior work suggesting that hybrid models scale more effectively (Waleffe et al., 2024; Jamba Team et al., 2024; Basant et al., 2025).

Compatibility of advanced primitives. Our work combined base Transformer and Mamba blocks, whereas recent models incorporate more advanced variants. For instance, some models (De et al. (2024), Ren et al. (2025), Qwen3-Next) employ self-attention variants like local (Beltagy et al., 2020), differential (Ye et al., 2024), and gated attention (Qiu et al., 2025), while others (Hou et al. (2025), Qwen3-Next) use linear attention mechanisms such as RWKV-7(Peng et al., 2025) or Gated DeltaNet (Yang et al., 2024). A key question is whether our design insights still apply to these newer hybrids and if the advantages of each component are preserved when combined.

Modality extension. To achieve superintelligence, models must move beyond language to internalize the laws of physics that govern our world through video modality. This shift to multimodal learning (e.g., video, audio) intensifies the need for architectures that can support tokenization-free processing (Yu et al., 2023; Pagnoni et al., 2024; Assran et al., 2025) and overcome long-context bottlenecks. Consequently, hybrid architectures incorporating SSMs are rapidly gaining traction, making their extension beyond the language domain a critical next step.

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Appendix

A Detailed Experimental Results

We will release the detailed settings and experimental results for each experiment soon. The code is also planned to be made publicly available.

B The Use of Large Language Models

We used large language models based on Llama 3.2 (Llama Team, 2024) and Llama 4 to polish the overall writing after drafting the paper ourselves. Additionally, we utilized the same models for vibe coding when fixing bugs or when making the initial drafts of the figures.

C Details for Computational and Memory Costs Comparison

FLOPs per sample. Most parameters are linear weight matrices, so total FLOPs can be estimated by multiplying the parameter count by $6L_{\rm ctx}$ (accounting for addition, multiplication, and forward / backward passes, with the backward pass being roughly twice as expensive as the forward pass). For Transformer, attention further adds FLOPs from query-key dot products and value scaling, totaling $12N_Ld_{\rm model}L_{\rm ctx}(L_{\rm ctx}+1)/2$, considering only causal attention and excluding Flash-Attention overhead (Dao et al., 2022). In SWA, FLOPs depend on the number of activated tokens based on window and sink sizes. Mamba, on the other hand, introduces additional FLOPs from its work-efficient parallel scan algorithm (Blelloch, 1990; Smith et al., 2022), calculated as $3L_{\rm ctx}(9d_{\rm ssm}d_{\rm state}+2d_{ssm})$. Thus, FLOPs per sample scale quadratically with sequence length ($L_{\rm ctx}$) for Transformer, while Mamba scales linearly. For a 1B model with 8K context, Mamba uses about 18% fewer FLOPs per sample than a Transformer.

Parameter counts. The attention in Transformer block uses four projection weights—query, key, value, and output. Variants like GQA reduce parameter count by decreasing the number of key and value heads, shrinking the corresponding projection matrices. In contrast, Mamba featurizes the input for state space parameters using several projection weights and 1D convolution layers, typically projecting the hidden dimension to twice its original size (i.e., $d_{\rm ssm} = d_{\rm model}$). It also includes time-invariant parameters **A** and **D**, as well as gating and output projection weights. As a result, when comparing only the attention components (excluding FFN), Mamba's parameter count is approximately 2.5 times higher than that of a Transformer block in a 1B model (e.g., 25M vs. 10M parameters per block).

Cache size. Cache size is a major inference bottleneck due to the GPU memory hierarchy, increasing HBM–SRAM communication (Dao et al., 2022). In Transformer, the cache consists of key and value states. The cache size is $4N_Ld_{\rm head}N_{\rm kv}L_{\rm ctx}$, where 4 accounts for key, value, and 2 bytes per bfloat16 element. Meanwhile, Mamba maintains two types of caches: hidden states for convolution layer and memory states compressed into a finite space. Its total cache size is $2N_L(d_{\rm ssm}d_{\rm state}+N_{\rm conv}(2d_{\rm state}+d_{\rm ssm}))$, with bfloat16 precision. Notably, Mamba's cache size is independent of sequence length, so its efficiency benefits increase with longer contexts. For a 1B model with 8K context, Mamba's cache footprint is about 95% smaller than a Transformer's (e.g., 256 MiB vs. 13.4 MiB).

D Detailed Experimental Setup

Model architecture details. Each model is constructed based on the Llama-based Transformer (Llama Team, 2024) and the Mamba architectures (Dao and Gu, 2024). We primarily follow to the configurations of Llama 3.2 and Mamba 2 across various model scales. Table 6 provides a summary of the detailed architectures for both the Transformer and Mamba models, which serve as the foundational computational primitives for our hybrid architecture variants.

		Base Configuration								Self-Attention		SSM			
Models	Sizes	N-emb	Emb	Vocab	N_L	$d_{ m model}$	$d_{ m ffn}$	$N_{ m head}$	N_{kv}	$d_{ m head}$	$d_{ m ssm}$	$d_{ m head}$	$d_{ m state}$	$N_{ m conv}$	
Llama	100M	0.10B	0.13B	128K	8	1024	3072	16	4	64	_	-	-	_	
	350M	0.35B	0.20B	128K	14	1536	4096	24	8	64	-	-	-	-	
	1B	0.97B	0.26B	128K	16	2048	8192	32	8	64	-	-			
	3B	2.78B	0.39B	128K	28	3072	8192	32	8	96	-	-	-	-	
	100M	0.10B	0.13B	128K	6	1024	3072	16	-	-	2048	128	128	4	
Mamba	350M	0.37B	0.20B	128K	11	1536	4096	24	-	-	3072	128	128	4	
	1B	0.98B	0.26B	128K	13	2048	8192	32	-	-	4096	128	128	4	
	3B	2.80B	0.39B	128K	21	3072	8192	32	-	-	6144	192	256	4	

Table 6 Architectural configurations for Transformer and Mamba models across different scales. For clarity, we separately detail the specific configurations for Self-Attention and SSM components. When constructing the inter- and intra-layer hybrid architectures, we refer to these configurations as the base computational primitives. The sliding window attention models use a window size of 512 and an attention sink size of 64 under the same Llama configuration.

Training settings. We conduct experiments using TorchTitan (Liang et al., 2024), a PyTorch-native platform designed for large-scale training of LLMs. We pretrain different hybrid models variants from scratch on DCLM-Baseline pretraining dataset (Li et al., 2024), which contains 4T tokens from 3B documents. We pretrain on randomly sampled 60B tokens using 8 H200 GPUs by default. We pack the corpus using the Llama 3.2 tokenizer (Llama Team, 2024), which has a vocabulary size of 128K. A bos token is prepended to every sample before packing them into a context length of 8K tokens. We enable the model to attend to all previous tokens, not just those within the same document, while the eos token is used to distinguish document boundaries. We employ only FSDP (Zhao et al., 2023) with a degree equal to the number of GPUs, and activation checkpointing to reduce memory footprint. We also utilize torch.compile (Ansel et al., 2024) to accelerate training. We use a batch size of 2M tokens and utilize a trapezoid learning rate scheduler (Xing et al., 2018) consisting of warmup (about 25%), stable, and cool down (about 20%) phases. The AdamW optimizer (Loshchilov and Hutter, 2017) and gradient clipping are used for all experiments. For the different model scales—100M, 350M, 1B, and 3B parameters—the learning rates are set to 6e-3, 3e-3, 6e-4, and 3e-4, respectively.

Evaluation settings. To assess model quality, we evaluate language modeling performance on the validation set of DCLM-Baseline (Li et al., 2024) and the PG19 datasets (Rae et al., 2019b). Additionally, following the settings of prior work (Gemini Team et al., 2024; Ho et al., 2024), we conduct evaluations on the Needle-In-a-Haystack long-context benchmark (Kamradt, 2023; Kuratov et al., 2024). We further measure few-shot accuracy on five benchmarks using the Language Model Evaluation Harness (Gao et al., 2024): LAMBADA (LD), HellaSwag (HS), PIQA (PQ), ARC (Easy and Challenge), and OpenBookQA (OB). For all the few-shot datasets except LAMBADA, accuracy is normalized by the byte length of the target string. We adhere to the standard number of shots for each dataset. All evaluation experiments are performed on a single H200 GPU.