Hymba: A Hybrid-head Architecture for Small Language Models

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Abstract: We propose **Hymba**, a family of small language models featuring a hybrid-head parallel architecture that integrates transformer attention mechanisms with state space models (SSMs) for enhanced efficiency. Attention heads provide high-resolution recall, while SSM heads enable efficient context summarization. Additionally, we introduce learnable meta tokens that are prepended to prompts, storing critical information and alleviating the "forced-to-attend" burden associated with attention mechanisms. This model is further optimized by incorporating cross-layer key-value (KV) sharing and partial sliding window attention, resulting in a compact cache size. During development, we conducted a controlled study comparing various architectures under identical settings and observed significant advantages of our proposed architecture. Notably, **Hymba** achieves state-of-the-art results for small LMs: Our **Hymba-1.5B-Base** model surpasses all sub-2B public models in performance and even outperforms Llama-3.2-3B with 1.32% higher average accuracy, an 11.67× cache size reduction, and 3.49× throughput.

Models on Hugging Face: Hymba-1.5B-Base | Hymba-1.5B-Instruct

1. Introduction

Transformers, with their attention-based architecture, have become the dominant choice for language models (LMs) due to their strong performance, parallelization capabilities, and long-term recall through key-value (KV) caches [1]. However, their quadratic computational cost and high memory demands pose efficiency challenges. In contrast, state space models (SSMs) like Mamba [2] and Mamba-2 [3] offer constant complexity and efficient hardware optimization but struggle with memory recall tasks, affecting their performance on general benchmarks [4, 5]. While existing hybrid models that stack attention and SSM layers have demonstrated potential [6, 7], they can introduce bottlenecks when one layer type is not well-suited for specific tasks, requiring compensation from subsequent layers.

We propose Hymba, a novel LM architecture that integrates attention heads and SSM heads within the same layer, offering parallel and complementary processing of the same inputs. This hybrid-head approach allows each layer to simultaneously harness both the high-resolution recall of attention and the efficient context summarization of SSMs, increasing the model's flexibility and expressiveness in handling various types of information flows and memory access patterns.

To further enhance the achievable performance of Hymba, we introduce learnable meta tokens that are prepended to the input sequences and interact with all
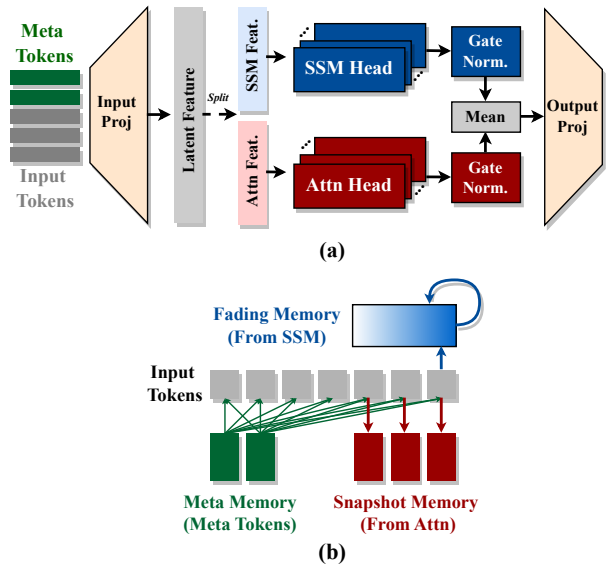

Figure 1 | (a) Visualize the hybrid-head module in Hymba; (b) Interpret from the memory aspect.

subsequent tokens even in sliding window attention. These meta tokens appear to act as a compressed representation of world knowledge and alleviate the issue of "softmax attention not being able to attend to nothing" [8, 9, 10], improving performance across both general and recall-intensive tasks.

Sharing KV cache between attention heads is common practice. Inspired by findings in [11] that consec-
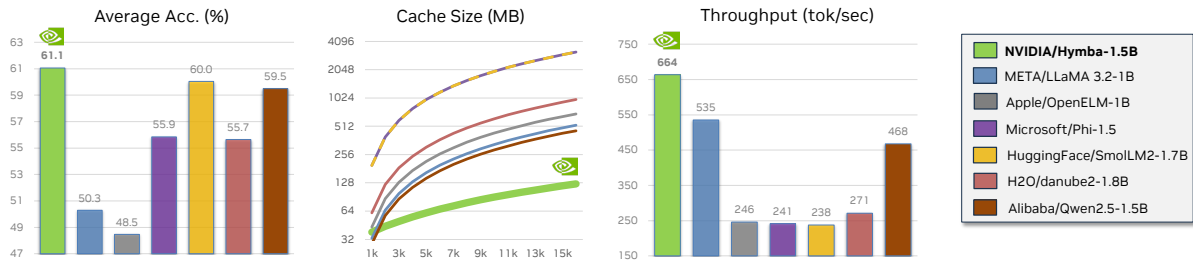
Figure 2 | Performance comparison of Hymba-1.5B against sub-2B models in terms of average task accuracy, cache size (MB) relative to sequence length, and throughput (tok/sec). Specifically, the tasks include 5-shot MMLU, ARC-C, ARC-E, PIQA, Hellaswag, Winogrande, and SQuAD-C, and the throughput is measured on an NVIDIA A100 with a sequence length of 8k and a batch size of 128 using PyTorch. For models encountering out-of-memory (OOM) issues during throughput measurement, we halve the batch size until the OOM is resolved. This approach is used to measure the maximal achievable throughput without OOM.

utive layers have a high correlation in the KV cache, we propose sharing the KV cache between layers as well. Additionally, for most layers, we choose sliding window attention to further minimize cache costs.

Comprehensive evaluations and ablation studies demonstrate that **Hymba** not only establishes new state-of-the-art (SOTA) benchmark performance across a wide range of representative tasks but also achieves greater efficiency compared to transformers and previous hybrid models. We provide the benchmark with other representative small LMs in Fig. 2, with more comprehensive benchmarks in Fig. 9. For instance, in commonsense reasoning tasks, **Hymba-1.5B** can outperform Llama-3.2-3B with 1.32% higher average accuracy, while requiring 11.67× smaller cache size and being 3.49× faster.

To optimize Hymba for on-device tasks, we employ supervised finetuning and direct preference optimization [12]. Our instruction-tuned model, Hymba-1.5B-Instruct, achieves best-in-class performance on GSM8K, GPQA, and the Berkeley function-calling leaderboard, surpassing Llama-3.2-1B. Additionally, parameter-efficient finetuning shows Hymba's strong potential in this setting. For instance, a DoRA [13]-finetuned version of Hymba-1.5B outperforms Llama3.1-8B-Instruct by 2.4% on RoleBench [14].

2. Hymba: The Proposed Hybrid-Head Architecture

SSMs such as Mamba [2] were introduced to address the quadratic complexity and large inference-time KV cache issues of transformers. However, due to their low-resolution memory, SSMs struggle with memory recall and performance [4, 15, 5]. To overcome these limitations, we propose a roadmap for developing efficient and high-performing small LMs in Tab. 1 and outlined as follows:

Fused hybrid modules. Fusing attention and SSM

Configuration	Commonsense Reasoning (%)	Recall (%)	Throughput (token/sec)	Cache Size (MB)	Design Reason
Ablations on 300M model size and 100B training tokens					
Transformer (Llama)	44.08	39.98	721.1	414.7	Accurate recall while inefficient
State Space Models (Mamba)	42.98	19.23	4720.8	1.9	Efficient while inaccurate recall
A. + Attention heads (sequential)	44.07	45.16	776.3	156.3	Enhance recall capabilities
B. + Multi-head structure (parallel)	45.19	49.90	876.7	148.2	Better balance of two modules
C. + Local / global attention	44.56	48.79	2399.7	41.2	Boost compute/cache efficiency
D. + KV cache sharing	45.16	48.04	2756.5	39.4	Cache efficiency
E. + Meta tokens	45.59	51.79	2695.8	40.0	Learned memory initialization
Scaling to 1.5B model size and 1.5T training tokens					
F. + Size / data	60.56	64.15	664.1	78.6	Further boost task performance
G. + Extended context length (2K→8K)	60.64	68.79	664.1	78.6	Improve multi-shot and recall tasks

Table 1 | Design roadmap of our Hymba model. We evaluate the models' (1) commonsense reasoning accuracy, averaged over 8 tasks, and (2) recall accuracy, averaged over 2 tasks, which corresponds to retrieving relevant information from past input. The throughput is on NVIDIA A100, sequence length 8k, batch size 128. The cache size is measured with a 8k sequence length, assuming the FP16 format.

heads in parallel within a hybrid-head module outperforms sequential stacking (Tab. 1 (A)-(B)). Both heads process the same information simultaneously, leading to improved reasoning and recall accuracy. We argue that sequential fusion lacks synergy, as both blocks operate on each set of inputs independently.

Efficiency and KV cache optimization. While attention heads improve task performance, they increase KV cache requirements and reduce throughput. To mitigate this, we optimize the hybrid-head module by combining local and global attention and employing cross-layer KV cache sharing, as shown in Tab. 1 (C) and (D). This improves throughput by 3× and reduces cache by almost 4×.

Meta Tokens – A set of 128 pretrained embeddings prepended to inputs, functioning as learned cache initialization to enhance focus on relevant information. These tokens serve a dual purpose: (i) they mitigate attention drain by acting as backstop tokens, redistributing attention effectively, and (ii) they encapsulate compressed world knowledge, see Tab. 1 (E) and Sec. 2.3.

Scaling – Ablation studies were performed on a 300M parameter model using 100B training tokens; the final models were trained with 1.5T tokens and scaled up to models with 350M and 1.5B parameters (see Tab. 1 (F)).

2.1. A Fused Hybrid-Head Module

SSM models are efficient but suffer from limited recall capabilities and task performance [4, 15, 5, 16] as seen in Tab. 1. Given the high recall resolution of attention, in this step we aim to (1) combine the processing efficiency and context summarization capabilities of SSMs with the high recall resolution of attention, and (2) develop a fused building block to achieve this goal, so it can serve as a fundamental component for constructing future foundation models.

Previous hybrid models [7, 17, 6] often combine attention and SSMs in a sequential manner. This strategy may lead to information bottlenecks when a layer type that is poorly suited for a specific task cannot effectively process the information. Motivated by the multi-head attention structure in the vanilla Transformer [1], where different heads undertake different roles and focus on different contexts [18, 19], we propose an alternative approach: *fusing attention and SSMs in parallel into a hybrid-head module*, as shown in Fig. 1 (a). The advantage of this design is that different attention and SSM heads can store, retrieve, and process the same piece of information in distinct ways, thereby inheriting the strengths of both operators.

Design formulation. We show that the hybrid-head module can be represented by a unified and symmetric formulation. As shown in Fig. 1 (a), given the input sequence $\tilde{X}$, which is the original input sequence X prepended with meta tokens introduced in Sec. 2.3, the input projection $W_{\text{in\_proj}} = [W^Q, W^K, W^V, W^{SSM}, W^G]$ projects $\tilde{X}$ to the query, key, and value of the attention heads using W^Q, W^K, and W^V, respectively, as well as the input features and gates of the SSM heads using W^{SSM} and W^G, respectively.

Following [1], the output of attention heads Y_{attn} can be formulated as:

$$Y_{\text{attn}} = \text{softmax}(QK^T)\,W^V \tilde{X} = M_{\text{attn}}\tilde{X} \quad (1)$$

where $M_{\text{attn}} = \text{softmax}(QK^T)\,W^V$ and $Q = W^Q\tilde{X}$, $K = W^K\tilde{X}$.

Similar to the attention heads, the SSM heads in our model, for which we adopt Mamba [2], can also be represented using a data-controlled linear operator M_{ssm}, following [20, 16]. Specifically, the SSM head output Y_{ssm} can be formulated as:

$$\alpha^{i,j} = C_i \left(\prod_{k=j+1}^{i} \exp(A\Delta_k) \right) B_j \Delta_j,$$
$$Y_{\text{ssm}} = G \odot \alpha(A, B, C, \Delta)\, W^{SSM} \tilde{X} = M_{\text{ssm}}\tilde{X}, \quad (2)$$

where $M_{\text{ssm}} = G \odot \alpha(A, B, C, \Delta)\, W^{SSM}$, $G = W^G\tilde{X}$ is an output gate, and A, B, C, Δ are the SSM parameters following the definition in [2]. More specifically, A is a learnable matrix, $B = W_B X_{ssm}$, $C = W_C X_{ssm}$, and $\Delta = \text{Softplus}(W_\Delta X_{ssm})$ with $X_{ssm} = W^{SSM}\tilde{X}$.

We observed that the output magnitudes of the SSM heads, Y_{ssm}, are consistently larger than those of the attention heads, Y_{attn}, as visualized in Fig. 12 in Append. B. To ensure effective fusion, we normalize and re-scale them using learnable vectors to improve training stability, and then average the outputs, followed by a final output projection. The overall formulation of our fused module can be represented symmetrically:

$$Y = W_{\text{out\_proj}} \left(\beta_1 \text{norm}(M_{\text{attn}}\tilde{X}) + \beta_2 \text{norm}(M_{\text{ssm}}\tilde{X}) \right) \quad (3)$$

where β_1 and β_2 are learnable vectors that re-scale each channel of the outputs from the attention and SSM heads, respectively. We further explore the optimal ratio of SSMs and attention in hybrid heads, along with their fusion strategy, in Append. B.

Interpretation from the memory aspect. The components in the hybrid-head module can be interpreted as analogous to human brain functions. Specifically, as shown in Fig. 1 (b), the attention heads

provide high recall resolution and thus act like snapshot memories in the human brain, storing detailed recollections of a moment or event. In contrast, the SSM heads summarize the context through a constant cache and thus function as fading memories, which gradually forget the details of past events while retaining their core or gist. As shown in Tab. 10 in Append. B, in our Hymba, the summarized global context from fading memories enables allocating more snapshot memories for memorizing local information while maintaining recall capabilities. This is achieved by replacing most global attention with local attention, thus improving memory efficiency.
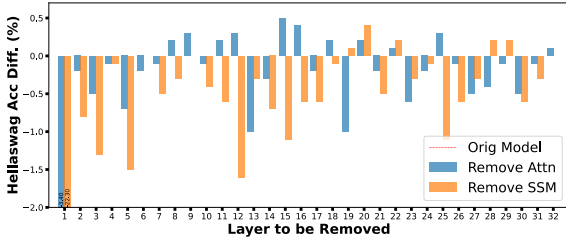

Figure 3 | Visualize the accuracy difference, measured using 1000 samples from Hellaswag [21], after removing the Attention or SSM heads in each layer.

Head importance analysis. We analyze the relative importance of attention and SSM heads in each layer by setting β_1 or β_2 in Eq. 3 to 0 and recording the final accuracy. We present the results on Hellaswag [21] in Fig. 3 and on more tasks in Fig. 13 in Append. C. We find that (1) the relative importance of attention/SSM heads in the same layer is input-adaptive and varies across tasks, suggesting that they can serve different roles when handling various inputs; (2) The SSM head in the first layer is critical for language modeling, and removing it causes a substantial accuracy drop to random guess levels; (3) Generally, removing one attention/SSM head results in an average accuracy drop of 0.24%/1.1% on Hellaswag, respectively.

2.2. KV Cache Optimization

Our hybrid-head module improves recall and reasoning capabilities but can compromise memory and throughput efficiency due to the KV cache required by the attention heads. To address this, we aim to reduce the KV cache while maintaining comparable task performance.

Combine global and local attention. Local attention, also known as Sliding Window Attention (SWA) [22], offers a more efficient alternative to global full attention, though it risks losing global context. However, with the presence of SSM heads in our hybrid-head module, which already summarize global
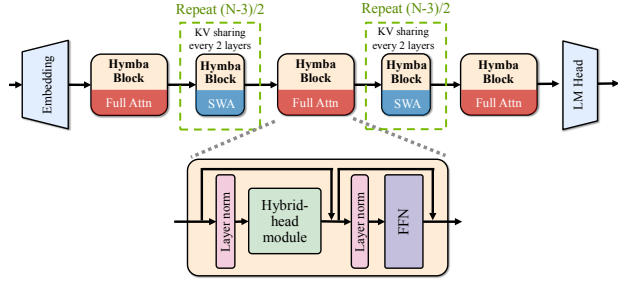

Figure 4 | (a) The overall architecture of our Hymba model; (b) The building block of Hymba.

context, we can more aggressively replace global full attention with local attention, achieving a better balance between efficiency and performance.

Exploring the ratio of local attention and global attention. As shown in Tab. 10 in Append. B, we initially replace global attention in all layers with SWA, which results in a significant degradation in recall capabilities, with accuracy dropping by over 20% on recall-intensive tasks. In response, we progressively reinstate global attention in some layers. Interestingly, as shown in Tab. 1 (C), we find that using global attention in just three layers (i.e., the first, middle, and last layers) is sufficient to recover recall-intensive accuracy while maintaining comparable commonsense reasoning accuracy. In turn, this strategy achieves 2.7× throughput and 3.8× cache reduction.

Cross-layer KV sharing. Recent works [23] observe that KV cache shares a high similarity between adjacent layers, suggesting that using separate KV caches for each layer leads to both cache and parameter redundancy. In light of this, we employ cross-layer KV sharing [11], where keys and values are shared between consecutive layers (e.g., every two layers share the same KV cache). This strategy reduces both KV memory usage and model parameters, allowing the saved parameters to be reallocated to other model components. As shown in Tab. 1 (D), cross-layer KV sharing improves throughput by 1.15× while maintaining comparable recall accuracy and boosting commonsense accuracy by +0.60%.

After the above optimization, Hymba's overall architecture is visualized in Fig. 4.

2.3. Meta Tokens

We observed that the initial tokens, though not semantically important, often receive significant attention scores from subsequent tokens, similar to observations in prior work [10, 27]. As shown in Fig.7, more than 50% of the attention is focused on the BOS token for Llama3.2-3B. To address this, we aim to
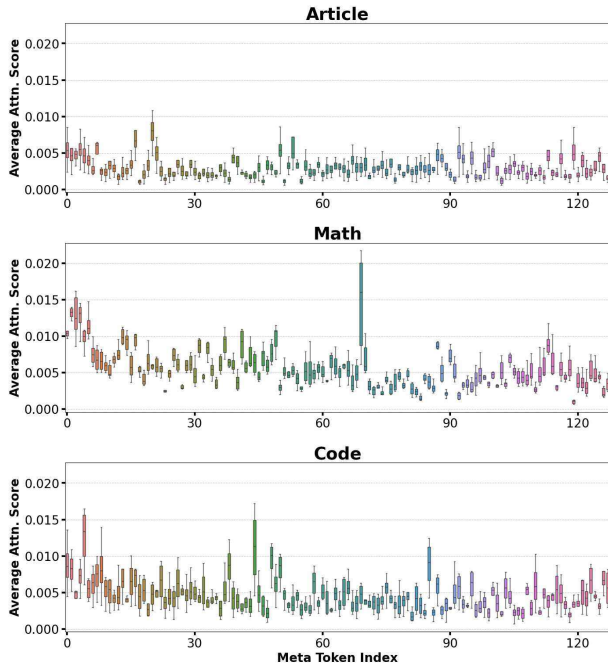
Figure 5 | Averaged attention scores received by the meta tokens in the last layer of Hymba-1.5B model. Prompts of 'Article', 'Math' and 'Code' are from SQuAD [24], GSM8K [25], and GitHub-Code [26] datasets, respectively.

guide the attention to focus more on tokens that meaningfully contribute to task performance. Specifically, we introduce a set of learnable meta tokens $R = [r_1, r_2, \ldots, r_m]$ to serve as the initial tokens. Given the input sequence $X = [x_1, x_2, \ldots, x_n]$, these meta tokens are prepended to the input sequence, forming the modified input sequence:

$$\tilde{X} = [R, X] = [r_1, r_2, \ldots, r_m, x_1, x_2, \ldots, x_n] \quad (4)$$

where $\tilde{X}$ represents the new input sequence for our model. At inference time, since the meta tokens are fixed and appear at the beginning of any input sequences, their computation can be performed offline. Thus, the role of meta tokens at inference can also be viewed as *learned cache initialization* to modulate the subsequent tokens, allowing subsequent tokens to focus more on those that contribute meaningfully to task performance.

Interpretation from the memory aspect. Similar to the analogy in Sec. 2.1, the meta tokens participate in the attention and SSM calculations of all subsequent tokens, analogous to metamemory in the human brain, which helps recognize where to locate needed information in other memories. To see this, we visualize the averaged attention scores received by the meta tokens in Fig. 5 for a Hymba-1.5B model. We observe that when the prompts are from different domains (e.g., article, math, and codes), different meta
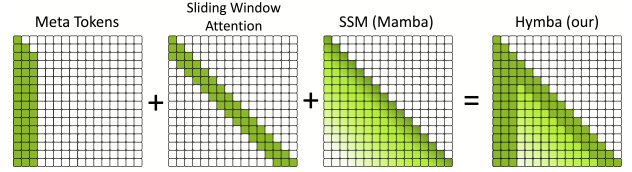

Figure 6 | Schematics of the attention map of Hymba as a combination of meta tokens, sliding window attention, and Mamba contributions.
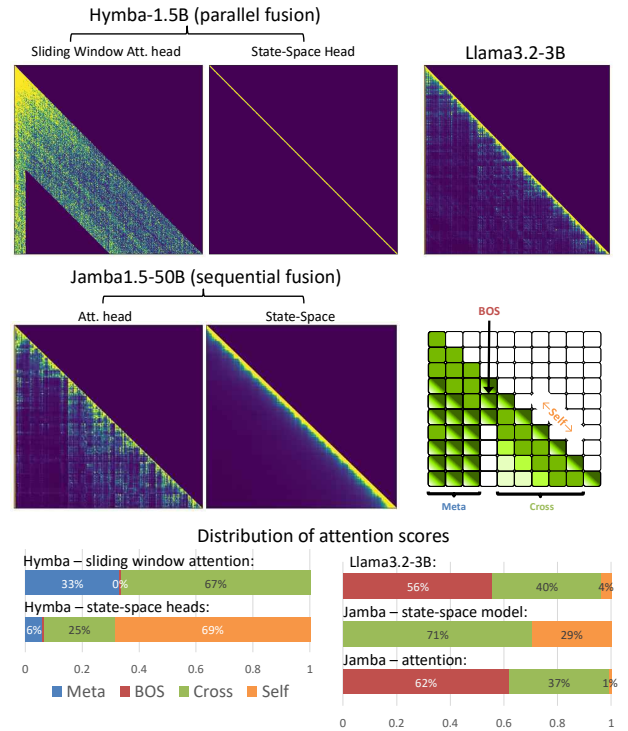

Figure 7 | Sum of attention score from different categories (i.e., 'Meta', 'BOS', 'Self', 'Cross') in Llama-3.2-3B, Jamba and Hymba-1.5B. Parallel SSM and Attention fusion in the latter disentangles attention.

tokens are activated. This suggests that different meta tokens encapsulate different world knowledge, which can be leveraged to guide the attention mechanism to focus on relevant information. We further analyze others roles of meta tokens and their connections with related works in Append. D.

The role of Meta Tokens. We hypothesise, that they perform the following functions. *Prevent token overwriting.* As shown in [30], attention tends to overwrite and over-attend to some tokens, acting as a garbage collector. Adding learnable tokens allowed for much more representative feature maps. Later, the same phenomenon was discovered in LLMs and named "attention sinks" [10, 27]. Therefore, the model should be provided with tokens that are independent of the input.

Exit tokens to deal with "forced-to-attend". Prepending tokens to the input affects the shape of the soft-

Table 2 | Benchmark Hymba with SOTA small LMs. All models have fewer than 2B parameters, except for Llama-3.2-3B, which is marked as gray. All results are obtained through LM-EVALUATION-HARNESS [28]. SQuAD-C (SQuAD-Completion) indicates a variant of the SQuAD question answering task proposed by [29]. The throughput is measured with a 8k sequence length and a 128 batch size on an NVIDIA A100 GPU. The best results are highlighted in **bold**, and the second-best results are highlighted in <u>underline</u>, where Llama-3.2-3B is not included in the ranking due to its 3B model size.

Model	#Params.	Train tokens	Token/s	Cache (MB)	MMLU 5-shot	ARC-E 0-shot	ARC-C 0-shot	PIQA 0-shot	Wino. 0-shot	Hella. 0-shot	SQuAD-C 1-shot	Avg.
OpenELM-1	1.1B	1.5T	246	346	27.06	62.37	19.54	74.76	61.80	48.37	45.38	48.47
Rene-v0.1	1.3B	1.5T	800	113	32.94	67.05	31.06	76.49	62.75	51.16	48.36	52.83
Phi-1.5	1.3B	0.15T	241	1573	42.56	76.18	<u>44.71</u>	76.56	**72.85**	48.00	30.09	55.85
SmolLM	1.7B	1T	238	1573	27.06	76.47	43.43	75.79	60.93	49.58	45.81	54.15
Cosmo	1.8B	0.2T	244	1573	26.10	62.42	32.94	71.76	55.80	42.90	38.51	47.20
h2o-danube2	1.8B	2T	271	492	40.05	70.66	33.19	76.01	<u>66.93</u>	**53.70**	49.03	55.65
Llama-3.2-1B	1.2B	9T	535	262	32.12	65.53	31.39	74.43	60.69	47.72	40.18	50.29
Qwen2.5	1.5B	18T	469	229	**60.92**	75.51	41.21	75.79	63.38	50.20	49.53	59.51
AMD-OLMo	1.2B	1.3T	387	1049	26.93	65.91	31.57	74.92	61.64	47.30	33.71	48.85
SmolLM2	1.7B	11T	238	1573	50.29	**77.78**	<u>44.71</u>	77.09	66.38	53.55	<u>50.50</u>	<u>60.04</u>
Llama-3.2-3B	3.0B	9T	191	918	56.03	74.54	42.32	76.66	69.85	55.29	43.46	59.74
Hymba	1.5B	1.5T	664	79	<u>51.19</u>	<u>76.94</u>	**45.90**	**77.31**	66.61	<u>53.55</u>	**55.93**	**61.06**

max function by modifying the denominator. Quiet Attention [31] modifies the softmax denominator by adding one, allowing the attention to output zeros. Adding one is equivalent to prepending an all-zero token to the keys and values. Our meta tokens take this idea further by being learnable, allowing to learn an optimal softmax shape.

Initialization for KV cache and SSM state. Learning initial tokens can be seen as a form of learned prompt tuning [32, 33] or learned initialization. For inference, meta tokens are fixed, and the keys and values can be precomputed offline and stored. Task-specific meta tokens can be used, though in this work we use one set for all tasks.

Meta tokens boost recall capabilities and commonsense reasoning accuracy. To analyze the impact of meta tokens on the attention mechanism, we visualize the entropy of the attention map for both the attention and SSM heads [20, 16] before and after introducing meta tokens. Specifically, the attention map entropy reflects the distribution of attention scores across tokens, where lower entropy indicates stronger retrieval effects [7], as the attention scores are concentrated around a smaller subset of tokens, and vice versa.

We provide the visualization in Fig. 15 in Append. D, where we observe that, after introducing meta tokens, both the attention and SSM heads exhibit an overall reduction in entropy. Combined with the improved reasoning and recall capabilities shown in Tab. 1 (E), this suggests that meta tokens may help both the attention and SSM heads focus more on a subset of important tokens that contribute most to task performance.

2.4. Hymba Attention Map

Hymba's attention pattern (Fig. 6) can be viewed as a combination of individual components from sliding window attention, meta tokens, and SSM.

We further categorize elements in the attention map into four types: (1) 'Meta': attention scores from all real tokens to meta tokens. This category reflects the model's preference for attending to meta tokens. In attention map, they are usually located in the first few columns (e.g., 128 for Hymba) if a model has meta tokens. (2) 'BOS': attention scores from

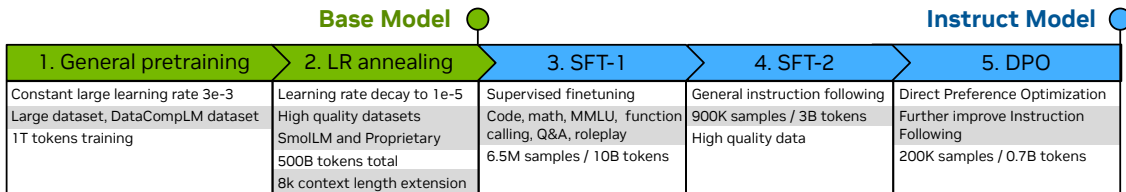| 1. General pretraining	2. LR annealing	3. SFT-1	4. SFT-2	5. DPO
Constant large learning rate 3e-3	Learning rate decay to 1e-5	Supervised finetuning	General instruction following	Direct Preference Optimization
Large dataset, DataCompLM dataset	High quality datasets	Code, math, MMLU, function calling, Q&A, roleplay	900K samples / 3B tokens	Further improve Instruction Following
1T tokens training	SmolLM and Proprietary	6.5M samples / 10B tokens	High quality data	200K samples / 0.7B tokens
	500B tokens total			
	8k context length extension			

Base Model ●   Instruct Model ●

Figure 8 | Training pipeline adapted for Hymba family. For detailed loss curve of Hymba-Base-1.5B see Fig 14.

all real tokens to the beginning-of-sequence token. In the attention map, they are usually located in the first column right after the meta tokens. (3) 'Self': attention scores from all real tokens to themselves. In the attention map, they are usually located in the diagonal line. (4) 'Cross': attention scores from all real tokens to other real tokens. In the attention map, they are usually located in the off-diagonal area.

In Fig. 7, we visualize the real attention maps from Llama-3.2-3B and Hymba-1.5B on texts from Oliver Twist Chapter 29 [34] and sum up the attention scores from different categories. The summed scores are normalized by the context length. For SSM heads, we follow Ben-Kish et al. [16] and Zimerman et al. [35] to calculate their attention maps and normalize the attention maps to ensure each row sums to 1.

We observe that the attention pattern of Hymba is significantly different from the vanilla Transformers. In vanilla Transformers, attention scores are more concentrated on 'BOS', which is consistent with the findings in [10]. In addition, vanilla Transformers also have a higher proportion of 'Self' attention scores. In Hymba, meta tokens, attention heads and SSM heads work complimentary to each other, leading to a more balanced distribution of attention scores across different types of tokens. Specifically, meta tokens offload the attention scores from 'BOS', allowing the model to focus more on the real tokens. SSM heads summarize the global context, which focus more on current tokens (i.e., 'Self' attention scores). Attention heads, on the other hand, pay less attention to 'Self' and 'BOS' tokens, and more attention to other tokens (i.e., 'Cross' attention scores). This suggests that the hybrid-head design of Hymba can effectively balance the attention distribution across different types of tokens, potentially leading to better performance.

2.5. Hymba Model Family

Building on the design insights explored above, we scale up the model sizes and training tokens to deliver the Hymba model family, which includes a 125M model, a 350M model, and a 1.5B model.

We train Hymba-125M/350M/1.5B models using a mix of DCLM-Baseline-1.0 [36], SmoLM-Corpus [37], and a proprietary high-quality dataset, with 1T, 250B, and 50B tokens, respectively. We combine the Warmup-Stable-Decay (WSD) learning rate scheduler [38], with maximum and minimum learning rates of 3e-3 and 1e-5, and the data annealing technique [39, 40] to ensure stable pretraining. We use a sequence length of 2k and a batch size of 2M tokens throughout the training process until the last 100B tokens, where we increase the sequence length

to 8k and change the ROPE base following [41]. The overall training pipeline is illustrated in Fig. 8. More pretraining details are provided in Append. E.

3. Model Evaluations

3.1. Experiment Settings

Baselines. Our baselines include popular (small) LMs with quadratic attention (e.g., Llama 3.2 [42], SmolLM [43], SmolLM2 [44], AMD-OLMo [45], StableLM [46], Olmo [47], Cosmo [48], Phi-1.5 [49], H2O-Danube [50], OpenELM [51], and MiniCPM [38]), as well as hybrid models (e.g., Rene [52]).

Benchmark settings. We adopt two benchmarking settings: (1) In Sec. 3.2, we directly benchmark our delivered Hymba against SOTA public small LMs, and (2) in Sec. 3.3, we train different architectures from scratch with the same dataset, number of layers, model size, and training recipes.

Benchmark tasks. In addition to evaluating commonsense reasoning and recall-intensive tasks on our base models, we also evaluate our instruction-tuned models on downstream tasks such as math, function calling, and role-playing in Sec. 3.4.

3.2. Benchmark with SOTA Small LMs

We present the benchmark results of our Hymba models with parameter sizes of 125M, 350M, and 1.5B, compared to SOTA small language models within the same size range.

As highlighted in Tab. 2, with only 1.5T pretraining tokens, our Hymba-1.5B model achieves the best performance among all sub-2B LMs and demonstrates better throughput and cache efficiency compared to all transformer-based LMs, with this speedup becoming even more pronounced as the sequence length increases. For instance, compared to the strongest sub-2B baseline, SmolLM2-1.7B, trained on 11T tokens, our Hymba-1.5B, trained on only 1.5T tokens, achieves a 1.02% average accuracy improvement, a $19.91\times$ cache size reduction, and $2.79\times$ throughput. When comparing with small LMs trained on no more than 2T tokens, our model achieves a 5.21%/5.41% average accuracy improvement over the most competitive baselines, Phi-1.5 and h2o-danube2-1.8B, respectively. Additionally, our model even outperforms Llama-3.2-3B, with 1.32% higher average accuracy, an $11.67\times$ cache size reduction, and $3.49\times$ throughput.

We visualize the trade-offs between commonsense reasoning accuracy and cache size/throughput in Fig. 9. In addition, our delivered tiny LMs, Hymba-125M/350M, consistently outperform all LMs of com-
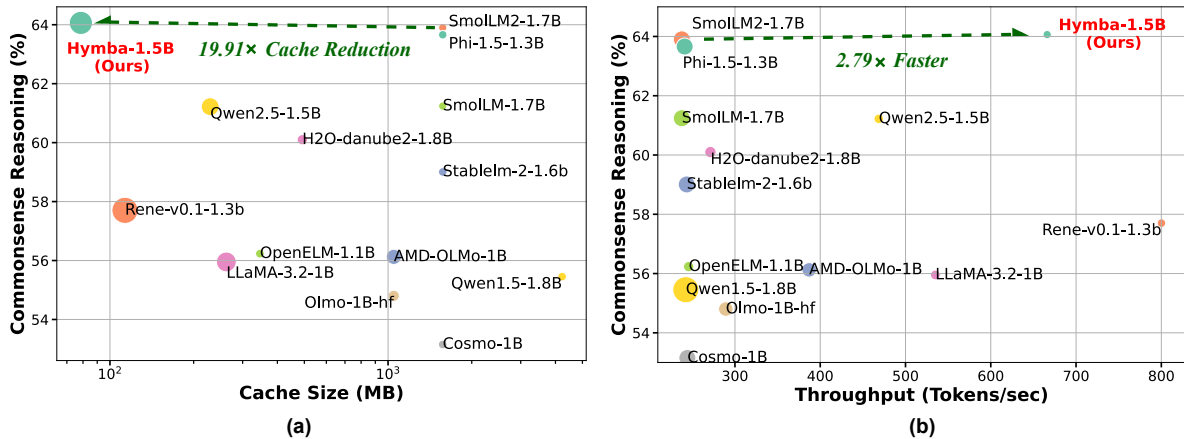
Figure 9 | Visualize the trade-off between (a) commonsense reasoning accuracy (avr. ARC-C, ARC-E, PIQA, Hellaswag, OBQA, and Winogrande using [28]) and cache size, with throughput represented by the point size of different models, and (b) commonsense reasoning accuracy and throughput, with cache size represented by the point size. The throughput is measured with a 8k sequence length and a 128 batch size on an NVIDIA A100 GPU. The cache size is measured with a 8k sequence length, assuming the FP16 format.

parable model size, as summarized in Tab. 6 and Tab. 7 in Append. A.1. We have also provided a Hymba-1.5B model trained exclusively on public data in Append. A.2.

3.3. Benchmark Different Architectures Under The Same Setting

General and recall-intensive tasks performance comparison. We do a comprehensive comparison between Hymba and other model architectures, including standard Transformer (Llama3 [53]), pure Mamba [2, 3], Mamba with FFN and hybrid architecture with sequential layer stacking (Samba [7]) on several downstream tasks. All models have the same number of layers and total parameters to facilitate equal comparison. Models are trained on the same data with the same hyperparameters and under the same codebase. To ensure our conclusions are generally valid, we run comparison experiments at different scales (1B and 300M) and different training datasets (SmolLM-corpus [37] and FineWeb [54]) in Tab. 3 and Tab. 9, respectively. We evaluate the models on language modeling, real-world recall-intensive, commonsense reasoning, and question-answering tasks.

As shown in Tab. 3, our Hymba model consistently outperforms other 1B architectures across most tasks, e.g., achieving an average score 1.45% higher than the second-best model at the 300M scale and 1.74% higher at the 1B scale. The ablation study for the 300M scale is in Append. A.

In addition, considering that Mamba models suffer from limited recall capabilities due to their constant-size cache and recurrent nature [16, 5, 15], we test the models on two real-world recall-intensive tasks, SWDE [5, 55] and SQuAD [5, 56], where the former is to to extract semi-structured relations from given raw HTML websites and the latter is to extract answers from a given context passages. Echoing the previous findings, Mamba2 and Mamba2 with FFN architectures under-perform the Transformer model (i.e. Llama3) on these tasks (see Tab. 3). Hymba model augments the Mamba heads with attention heads, which allows the model to have a large effective receptive field to establish long-range dependencies and high-resolution memory to store and retrieve key information in all layers. As a result, Hymba outperforms the Transformer and Samba architectures (where the latter stacks Mamba and attention layers sequentially).

Needle-in-the-Haystack performance comparison. We further do an apple-to-apple comparison between Hymba, Mamba2, and Llama3 on the synthetic retrieval task, needle-in-the-haystack. A random and informative sentence (i.e., needle) is inserted into a long document (i.e., haystack) and the model is required to retrieve the needle from the haystack to answer the questions. All models are of size 1B and trained with the same setting: (i.) pretrain is done with 1k sequence length; (ii.) finetune with 4k sequence length; (iii.) test with up to 16k sequence length. If model has ROPE, then we adjust the ROPE as in [57] during finetuning. As shown in Fig. 10, the Hymba model significantly outperforms the Mamba2 and Llama3 models. While the Mamba2 model has good extrapolation capabilities when the needle is inserted in the end of the haystack, it struggles to retrieve the needle when the needle is in the beginning

Task Type	Arch. Style (1B)	Mamba2	Mamba2 w/ FFN	Llama3	Samba	Hymba
Language	Wiki. ppl. ↓	<u>19.17</u>	20.42	19.28	19.91	**18.62**
	LMB. ppl. ↓	<u>12.59</u>	14.43	13.09	12.65	**10.38**
Recall Intensive	SWDE ↑	50.24	26.43	**75.95**	30.00	<u>54.29</u>
	SQuAD-C ↑	36.43	31.40	18.70	<u>42.33</u>	**44.71**
	Avg. ↑	43.34	28.92	<u>47.33</u>	36.17	**49.50**
Common-sense Reasoning and Question-answering	Lambda ↑	47.51	44.54	47.95	<u>49.08</u>	**52.84**
	PIQA ↑	<u>73.94</u>	73.07	73.45	73.23	**74.97**
	ARC-C ↑	38.91	37.03	<u>39.68</u>	39.59	**41.72**
	ARC-E ↑	70.96	71.00	<u>73.74</u>	73.36	**74.12**
	Hella. ↑	57.73	55.83	57.64	<u>58.49</u>	**60.05**
	Wino. ↑	**58.48**	55.56	56.20	57.54	<u>57.85</u>
	TruthfulQA ↑	30.75	29.86	<u>31.64</u>	28.84	**31.76**
	SIQA ↑	41.86	42.22	42.22	<u>42.48</u>	**43.24**
	Avg. ↑	52.52	51.14	52.82	<u>52.83</u>	**54.57**

Table 3 | Apple-to-apple comparison of our Hymba, pure Mamba2 [3], Mamba2 with FFN, Llama3 [39] style, and Samba- [7] style (Mamba-FFN-Attn-FFN) architectures. All models have 1B parameters and are trained from scratch for 100B tokens from SmolLM-Corpus [37] with exactly the same training recipe. All results are obtained through LM-EVALUATION-HARNESS [28] using a zero-shot setting by us on HuggingFace models. The best and second best results are highlighted in bold and underline, respectively.

or middle of the haystack. In contrast, Llama3 model has limited extrapolation capabilities [58, 57, 59] and struggles to the "lost in the middle" [60] scenario.
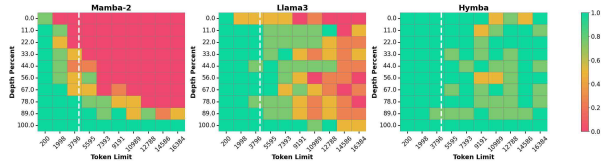

Figure 10 | Needle-in-the-haystack performance comparison across different architecture under apple-to-apple setting. The white vertical line represents the finetuning sequence length (4k).

3.4. Instruction-tuned Model

Implementation details of post-training. We post-trained Hymba-1.5B base model with a two-stage strategy: the first full-finetuning (FFT) stage and another direct preference optimization (DPO) [12] training. The learning rates are 5e-5, and 3e-6 for FFT and DPO, respectively. To accelerate training, we follow the training recipe [61, 62, 63] to pack the samples and use a block size of 8192. We compare Hymba-1.5B-Instruct with competitive lightweight instruction-tuned models, i.e., Llama-3.2-1B-Instruct [42], OpenELM-1-1B-Instruct [51], Qwen2.5-1.5B-Instruct [64], and SmolLM-1.7B-Instruct [43]. We test the instruction-tuned models on MMLU (5-shot), IFEval, GSM8K (5-shot), GPQA (0-shot), and Berkeley Function-Calling Leaderboard v2 (BFCLv2) [65]. More details about

the experimental settings, baseline models, and evaluation tasks are shown in Append. E.

Evaluation results. The evaluation results are shown in Tab. 4. In general, Hymba-1.5B-Instruct achieves the highest performance on an average of all tasks, outperforming the previous SoTA model, Qwen2.5-Instruct, by around 2%. It demonstrates a great ability in math, reasoning, and function calling, with the best-in-class performance.

Evaluation on role-play tasks. In addition to full finetuning, we conduct experiments to evaluate whether Hymba is compatible with DoRA [13], a parameter-efficient finetuning method that updates pretrained models using a minimal set of parameters. This approach is especially well-suited for on-device finetuning scenarios where computational resources are constrained. Additionally, DoRA significantly reduces storage requirements for saving multiple downstream models, as it only requires storing the finetuned DoRA parameters, which constitute less than 10% of the original model's total parameters. Specifically, we further finetune the post-trained Hymba on RoleBench [14] using DoRA to enhance its role-playing capabilities. The training set of RoleBench is used for training, and the model is evaluated on two sub-tasks: instruction generalization (Inst. Gene.) and role generalization (Role. Gene.). As shown in the Tab. 5, our Hymba-DoRA significantly outperforms larger models. For instance, DoRA finetuned Hymba achieves scores of 40.0% /

Table 4 | The comparison between lightweight instruction-tuned models. The best and second-best results are highlighted in bold and underlined, respectively. * OpenELM and SmolLM cannot understand function calling, leading to 0 accuracy in most categories.

Model	#Params	MMLU ↑	IFEval ↑	GSM8K ↑	GPQA ↑	BFCLv2 ↑	Avg. ↑
SmolLM	1.7B	27.80	25.16	1.36	25.67	-*	20.00
OpenELM	1.1B	25.65	6.25	<u>56.03</u>	21.62	-*	27.39
Llama-3.2	1.2B	44.41	**58.92**	42.99	24.11	20.27	38.14
Qwen2.5	1.5B	**59.73**	46.78	<u>56.03</u>	<u>30.13</u>	<u>43.85</u>	<u>47.30</u>
SmolLM2	1.7B	49.11	55.06	47.68	29.24	22.83	40.78
Hymba-1.5B	1.5B	<u>52.79</u>	<u>57.14</u>	**58.76**	**31.03**	**46.40**	**49.22**

Model	#Params	Instruction Generalization	Role Generalization
Llama-7B	7B	19.2	19.3
Aplaca-7B	7B	25.6	24.5
Vicuna-13B	13B	25.0	24.3
Llama2-7B-chat	7B	18.8	20.5
RoleLlama-7B	7B	35.5	33.5
Hymba-DoRA	1.5B	**40.0**	**37.9**

Table 5 | The comparison between DoRA-finetuned Hymba and baselines on RoleBench. All baseline results are from [14].

37.9% on instruction generalization/role generalization, outperforming RoleLlama-7B [14] by 4.5%, and 4.4% respectively. This indicates the strong generalization of our model and the effectiveness of using parameter-efficient finetuning techniques to further enhance its performance.

4. Related Works

Large language models. Prior to the rise of LLMs, transformer-based models [1, 66, 67, 68] proved highly effective at capturing relationships between tokens in complex sequences through the use of the attention mechanism [1]. These models also demonstrated considerable scalability [69, 70, 71] in terms of both model size and the volume of pretraining data. This scalability paved the way for the development of LLMs, such as GLM [72], OPT [73], Mistral [74], the Llama series [75, 53], Gemma [76], and GPT-4 [77], which showcase remarkable zero-shot and few-shot in-context learning abilities.

Efficient language model architectures. Despite the promise of transformer-based LMs, the quadratic computational complexity and the linearly increasing KV cache size of attention modules with longer sequences limit their processing efficiency. To address this, efficient LMs featuring sub-quadratic complexity in sequence length and strong scaling properties have emerged [78, 79, 2, 3, 80, 81]. As pointed out by [2], popular efficient LM architectures such as RWKV [78] and RetNet [79] can be viewed as vari-

ants of SSMs [82, 83]. These models utilize a linear dynamical system approach with a constant-size memory to recurrently encode past information, achieving linear scaling with sequence length. Mamba[2], one of the most widely used SSMs, improves upon previous SSMs by selectively propagating or forgetting information along the sequence length in an input-dependent manner. This approach outperforms transformers on several downstream tasks while offering faster inference. Follow-up works such as Mamba2 [3] and GLA [80] introduce more hardware-friendly gating mechanisms to enhance training throughput over Mamba. However, despite their promise, SSMs have been identified as having limited recall capabilities [4] and underperforming on in-context learning tasks [84].

Hybrid language models. To combine the processing efficiency of SSMs with the recall capabilities of transformers, an emerging trend is the creation of hybrid models that incorporate both types of operators. Specifically, [84] proposes a hybrid model called MambaFormer, which interleaves Mamba and attention modules to improve in-context learning capabilities. Similarly, [4] finds that introducing a small number of attention layers into a Mamba model can significantly enhance both commonsense reasoning and long-context capabilities. Jamba [6] and Zamba [17] develop sequentially stacked Mamba-Attention hybrid models. Jamba further integrates Mixture-of-Experts into the MLP layers, while Zamba employs a shared attention module. Both models demonstrate improvements in inference speed and task accuracy compared to previous transformer-based models of similar size. Samba [7] introduces a structure that sequentially stacks Mamba, SWA, and MLP layers by repeating the Mamba-MLP-SWA-MLP structure, achieving constant throughput as sequence lengths increase. Other recent work has also explored hybrid models that mix either linear RNNs or convolutions with attention [85, 86, 87, 88]. This work proposes a new hybrid model featuring a fused multi-head building block that stacks hybrid operators in parallel. Our model outperforms previous architectures, as demonstrated by

extensive benchmarking in Sec. 3.

5. Conclusion

In this work, we present Hymba, a new family of small LMs featuring a hybrid-head architecture that combines the high-resolution recall capabilities of attention heads with the efficient context summarization of SSM heads. To further optimize the performance of Hymba, we introduce learnable meta tokens, which act as a learned cache for both attention and SSM heads, enhancing the model's focus on salient information. Through the roadmap of Hymba, comprehensive evaluations, and ablation studies, we demonstrate that Hymba sets new SOTA performance across a wide range of tasks, achieving superior results in both accuracy and efficiency. Additionally, our work provides valuable insights into the advantages of hybrid-head architectures, offering a promising direction for future research in efficient LMs.

6. Acknowledgments

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A. Extensive Benchmark for More Hymba Model Variants

A.1. Comparison with SOTA Tiny LMs at 350M and 125M Scales

Besides our 1.5B model, we also evaluate the 350M and 125M Hymba models on a diverse set of benchmarks in Tab. 6 and Tab. 7, respectively. Consistent with the results of our 1.5B model, Hymba-350M/125M models outperform the SOTA tiny LMs across most of tasks and achieve the best average score. This indicates that our Hymba scales effectively across different model sizes.

A.2. Evaluating Hymba-1.5B Trained on Public Data Only

We have also trained our Hymba-1.5B model exclusively on public data and evaluated its performance. Specifically, following the training settings in Sec. 2.5, we train Hymba-1.5B on DCLM-Baseline-1.0 [36] for 1T tokens in the first phase and on SmoLM-Corpus [37] for 500B tokens in the second phase, keeping all other settings the same. The results are summarized in Tab. 8, where only the most competitive baselines from Tab. 2 are included. We observe that (1) Hymba-1.5B trained exclusively on public data only still surpasses all baseline small LMs in terms of average accuracy; and (2) Hymba-1.5B trained on public data primarily suffers from performance drops on 5-shot MMLU compared to the version trained on all data, including our proprietary dataset. This suggests that the public data used may lack sufficient factual knowledge, which is supplemented by our proprietary one.

A.3. Apple-to-Apple Comparison with Other Architectures at 300M Scale

In addition to the apple-to-apple architecture comparison under the same settings with a 1B model size in Sec. 3.3 of our main paper, we further validate the superiority of our architecture at the 300M size. Specifically, we train different 300M model architectures on 100B tokens from FineWeb [54]. We set peak learning rates to 5e-4 and use warmup and cosine decay scheduler. The training sequence length is set to 1K. For models with sliding window attention, we set the sliding window size as 256. As shown in Tab. 9, Hymba achieves the best performance in almost all tasks (with a second-best result in one task), yielding an average accuracy boost of +1.45% compared to the strongest baseline.

B. Ablation Studies of Our Hymba Architecture

We perform further ablation studies and analyses of the design factors in our Hymba.

Parallel vs. Sequential fusion

We compare the hybrid-head module with a sequential counterpart, which interleaves local attention and Mamba layers as adopted by [7], by calculating the models' effective receptive field (ERF) and their overall cache size. All the compared models have the same parameter size and are training from scratch using exactly the same training recipe. ERF is an empirical measure of the averaged distance among tokens that allows effective information propagation [16, 89] defined as the following,

$$ERF \approx \sum_{n \leq N} \sum_{h \leq H} \sum_{s \leq S} \frac{2M^h(S,s) \cdot (S-s) \cdot (N-n+1)}{HN(N+1)}, \quad (5)$$

where S is index of the last token in the sequence, N is index of the last layer in the model, and $M^h(S,s)$ is the normalized attention score between token s and the last token in head h.

As shown in Fig. 11, we observe that (1) in line with common intuitions, Llama3 exhibits a notably larger ERF compared to Mamba due to its higher recall resolution, albeit at the cost of a larger cache size; (2) our multi-head structure demonstrates the best ERF across the four designs, with an order of magnitude larger ERF while maintaining a cache size comparable to the sequential structure. This suggests that the parallel structure can better leverage the limited cache size to capture longer and more complex relationships among tokens compared to the sequential one. The differences in ERF are also reflected in task accuracy: According to Tab. 1, the multi-head design (Tab. 1 (B)) improves commonsense reasoning and recall accuracy by +1.08% and 4.74%, respectively, over the sequential design (Tab. 1 (A)). Based on this
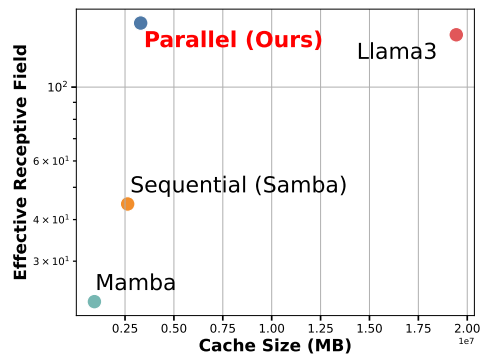

Figure 11 | Visualize the ERF and cache size trade-off.

Table 6 | Benchmark Hymba with SOTA tiny LMs, all of which have fewer than 200M parameters. All results are obtained through Huggingface/LightEval, following Ben Allal et al. [43].

Model	#Params.	MMLU (cloze) ↑	ARC (c+e) ↑	PIQA ↑	Hella. ↑	OBQA ↑	Wino. ↑	Avg. ↑
Mamba-130m-hf	130M	27.41	33.01	63.33	33.86	30.40	51.54	42.43
Cerebras-GPT	111M	25.56	27.75	58.16	26.32	25.40	50.28	37.58
GPT-neo	125M	27.25	31.30	62.35	29.68	29.20	51.54	40.81
LaMini-GPT	124M	26.47	33.26	62.89	30.05	27.80	50.75	40.95
Opt	125M	25.67	31.25	61.97	31.04	29.00	53.20	41.29
GPT2	137M	26.29	31.09	62.51	29.76	29.40	49.72	40.50
Pythia	160M	26.68	31.92	61.64	29.55	27.80	49.49	40.08
MobileLM	125M	-	35.51	65.30	38.90	**39.50**	**53.10**	46.46
SmolLM	135M	30.23	43.99	**69.60**	42.30	33.60	52.70	48.44
Hymba	125M	**31.12**	**44.95**	68.50	**45.54**	35.52	52.25	**49.35**

Table 7 | Benchmark Hymba with SOTA tiny LMs, all of which have fewer than 400M parameters. All results are obtained through Huggingface/LightEval, following Ben Allal et al. [43].

Model	#Params.	MMLU (cloze) ↑	ARC (c+e) ↑	PIQA ↑	Hella. ↑	OBQA ↑	Wino. ↑	Avg. ↑
Bloom	560M	27.49	32.86	65.13	35.98	28.80	51.70	42.89
Cerebras-GPT-256M	256M	25.91	29.69	61.37	28.44	28.00	51.62	39.82
Cerebras-GPT-590M	590M	26.93	32.40	62.84	31.99	28.40	50.12	41.15
Opt	350M	26.57	31.94	64.36	36.09	27.80	52.57	42.55
Pythia	410M	28.94	35.05	66.92	39.21	28.40	52.80	44.48
GPT2-medium	380M	27.77	34.30	66.38	37.06	31.20	49.49	43.69
MobileLM	350M	-	43.65	68.60	49.60	**40.00**	57.60	51.89
SmolLM	360M	34.17	51.10	72.00	53.80	37.20	53.70	53.56
Hymba	350M	**34.54**	**52.46**	**72.91**	**55.08**	38.40	**57.85**	**55.34**

benchmarking and analysis, we adopt the hybrid-head module as our basic building block.

The ratio of SSMs and attention in hybrid heads. To determine the proper number of attention heads, we start with a Mamba model and gradually replace Mamba's hidden dimensions with attention heads, maintaining the same overall model size. As shown in Tab. 10 (1)∼ (4), we observe that model performance improves as the ratio of attention parameters increases and gradually saturates when the parameter ratio of attention to Mamba reaches 1:2.12. We stop introducing more attention heads, considering that adding more would bring increased memory overhead.

There are two interesting observations: (1) Although the attention-only model outperforms the Mamba-only model, the hybrid model with both attention and Mamba heads achieves the best performance; (2) with further KV cache optimization, the ratio of attention heads decreases further. In our final model, attention heads occupy no more than

1/5 of the Mamba heads, yet significantly boost both recall and commonsense reasoning compared to the vanilla Mamba. This suggests that the hybrid model leverages the strengths and diversity of both attention and SSM heads, achieving a better trade-off between efficiency and performance.

The hybrid-head fusion strategy. We have explored two straightforward methods to fuse the outputs of attention and SSM heads: concatenation and mean. For concatenation, we combine the outputs of all heads and use a linear layer to project the concatenated output to the final output dimension. However, the parameter size of the linear layer increases with both the number of heads and the head dimensions. Additionally, based on the empirical comparison between Tab. 10 (9) and (11), the performance of concatenation fusion is not better than the simple mean fusion. Therefore, we adopt the mean fusion strategy in our final design.

Impact of KV cache optimization. After applying a series of KV cache optimization techniques,

Table 8 | Benchmark Hymba-1.5B trained with all data and public data only against SOTA small LMs. All models have fewer than 2B parameters, except for Llama-3.2-3B, which is marked in gray. The settings follow Tab. 2 in our main paper and we only include the most competitive baselines here. **Hymba (Public Data)** refers to our model trained exclusively on public datasets, without using our proprietary high-quality dataset.

Model	#Params.	Train tokens	Token/s	Cache (MB)	MMLU 5-shot	ARC-E 0-shot	ARC-C 0-shot	PIQA 0-shot	Wino. 0-shot	Hella. 0-shot	SQuAD-C 1-shot	Avg.
Phi-1.5	1.3B	0.15T	241	1573	42.56	76.18	44.71	76.56	**72.85**	48.00	30.09	55.85
h2o-danube2	1.8B	2T	271	492	40.05	70.66	33.19	76.01	66.93	53.70	49.03	55.65
Qwen2.5	1.5B	18T	469	229	**60.92**	75.51	41.21	75.79	63.38	50.20	49.53	59.51
SmolLM2	1.7B	11T	238	1573	50.29	77.78	44.71	77.09	66.38	53.55	50.50	60.04
Llama-3.2-3B	3.0B	9T	191	918	56.03	74.54	42.32	76.66	69.85	55.29	43.46	59.74
Hymba	1.5B	1.5T	664	79	51.19	76.94	45.90	77.31	66.61	53.55	55.93	**61.06**
Hymba (Public Data)	1.5B	1.5T	664	79	44.31	**78.58**	**47.01**	**77.53**	64.56	**53.89**	59.82	60.81

Table 9 | Apple-to-apple comparison of our Hymba, pure Mamba [2], Mamba with FFN, Llama3 [39] style, and Samba- [7] style (Mamba-FFN-Attn-FFN) architectures. All models have 300M parameters and are trained for 100B tokens from FineWeb dataset [54] with exactly the same training recipes. All results are obtained through LM-EVALUATION-HARNESS [28]. The best and second best results are highlighted in bold and underline, respectively.

Task Type	Arch. Style (300M)	Mamba	Mamba w/ FFN	Llama3	Samba	Hymba
Language	Wiki. ppl. ↓	30.78	33.41	30.04	31.41	**28.53**
	LMB. ppl. ↓	19.95	23.64	20.53	19.75	**15.45**
Recall Intensive	SQuAD-C ↑	21.31	17.56	22.10	39.88	**45.24**
	SWDE ↑	17.14	13.10	57.86	22.14	**58.33**
	Avg. ↑	19.23	15.33	39.98	31.01	**51.79**
Common-sense Reasoning and Question-answering	Lambda ↑	38.95	36.37	40.15	40.59	**44.67**
	PIQA ↑	69.64	69.26	70.29	69.86	**70.73**
	ARC-C ↑	24.91	25.00	24.83	25.76	**26.28**
	ARC-E ↑	50.67	50.34	50.24	49.79	**53.20**
	Hella. ↑	44.95	44.08	45.69	46.45	**48.23**
	Wino. ↑	51.70	51.78	52.64	52.49	**53.35**
	TruthfulQA ↑	23.86	26.23	**28.97**	27.27	27.87
	SIQA ↑	39.20	39.53	39.66	39.92	**39.92**
	Avg.	42.98	42.82	44.08	44.02	**45.53**

moving from Tab. 10 (5) to Tab. 10 (9), we observe that our Hymba maintains comparable recall and commonsense reasoning accuracy while being 2.74× faster. In contrast, applying the same KV cache optimization to a pure Transformer, as seen in the comparison between Tab. 10 (6) and (10), results in a recall accuracy drop of 10% or more and degraded commonsense reasoning accuracy. This supports our analysis in Sec. 2.2, showing that the presence of SSM heads in our hybrid-head module has already summarized the global context, allowing us to more aggressively replace global full attention with local attention in our hybrid model.
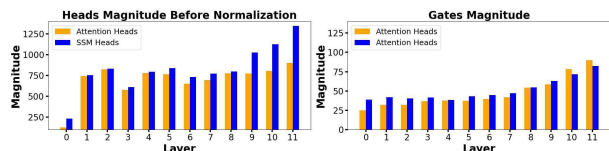

Figure 12 | Left: visualization of output magnitudes of attention and SSM heads. SSM heads consistently have higher output magnitude than attention heads due to their structure. Right: visualization of attention and SSM heads' gate magnitudes. Through model learning, the relative magnitudes of attention and SSM gates vary across different layers.

Table 10 | Ablation study of the design choices of Hymba. The design finally adopted by Hymba is highlighted in **bold**. Specifically, the task lists are the same as those in Tab. 3. The throughput is measured with a 8k sequence length and a 128 batch size on an NVIDIA A100 GPU. The cache size is measured with a 8k sequence length, assuming the FP16 format.

| Design Factor	Configuration		Param. Ratio Attn:Mamba	Avg. (General) ↑	Avg. (Recall) ↑	Throughput (Token/s) ↑	Cache (MB) ↓
Attn/Mamba Ratio	1)	Mamba Heads Only	0:1	42.98	19.23	4720.8	1.87
	2)	Mamba + 4 Attn Heads	1:8.48	44.20	44.65	3278.1	99.09
	3)	Mamba + 8 Attn Heads	1:4.24	44.95	52.53	1816.5	197.39
	4)	Mamba + 16 Attn Heads	1:2.12	45.08	56.46	656.6	394.00
	5)	**4) + GQA**	1:3.64	45.19	49.90	876.7	148.24
	6)	Attn Heads Only (Llama)	1:0	44.08	39.98	721.1	414.72
Sliding Window	7)	5) + All SWA's	1:3.64	44.42	29.78	4485.09	5.51
	8)	**5) + SWA's + Full Attn**	1:3.64	44.56	48.79	2399.7	41.19
	9)	**8) + Cross-layer KV sharing**	1:5.23	45.16	48.04	2756.5	39.42
	10)	6) + Same KV compression	1:0	43.60	28.18	3710.0	28.98
Fusion	11)	9) Replace Mean by Concat	1: 5.82	44.56	48.94	1413.9	39.42
Meta Tokens	12)	1) + Meta Tokens	0:1	44.01	19.34	4712.8	1.87
	13)	**9) + Meta Tokens**	1:5.23	45.53	51.79	2695.8	40.01
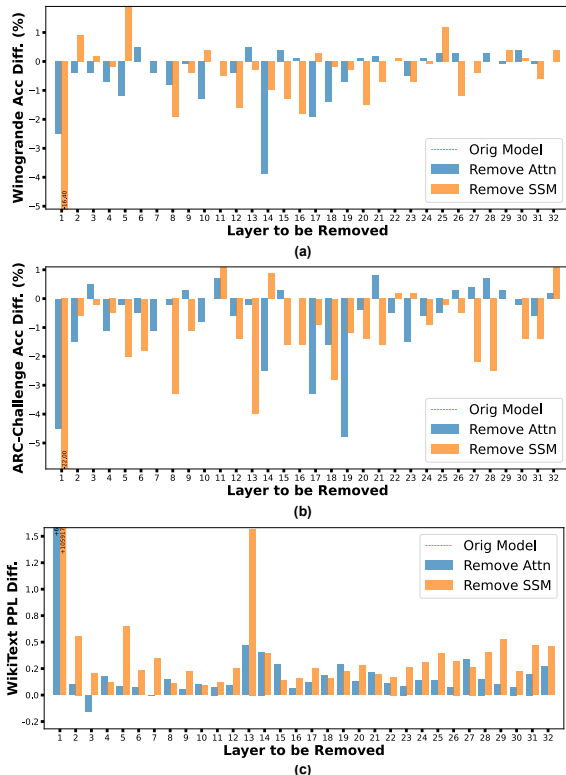
Figure 13 | Visualize the task performance difference across three tasks after removing the Attention or SSM heads in each layer. The task performance is measured using 1000 samples from each task. Note that removing critical modules in specific layers causes a significant gap compared to others, making their bars fall outside the box. For such layers, we annotate the task performance with text.

C. Head Importance Analysis

Setup. To understand how hybrid heads contribute to the final task performance, we zero out the at-

tention or SSM heads in each layer by setting β_1 or β_2 in Eq. 3 to 0 and record the final accuracy. We consider four datasets, which are presented in Fig. 3 and Fig. 13, and the task performance is measured using 1000 samples from each task, evaluated with lm-evaluation-harness [28] in a zero-shot setting.

Observations. As shown in Fig. 13, we observe that (1) the relative importance of attention/SSM heads in the same layer, indicated by the change in task performance before and after being removed, may vary across different tasks. In other words, the relative importance of attention/SSM heads in the same layer is input-adaptive, indicating that different types of heads learn to serve different roles and undertake different responsibilities when handling various inputs; (2) The SSM head in the first layer is critical for language modeling and removing it causes a substantial increase in PPL or a substantial drop in accuracy (to random guess levels). Generally, removing one attention/SSM head results in a 0.46%/1.2% reduction in accuracy averaged across all layers and tasks, respectively.

D. Meta Tokens: More Analysis and Visualization

Relationship with prior works. Learnable tokens have also been leveraged in previous transformer-based models. Previous prompt tuning works [32, 33] prepend learnable prompts while keeping the model weights frozen during the task-specific tuning stage, aiming to adapt a pretrained LM to downstream tasks in a parameter-efficient manner. [90] introduces both learnable tokens and corresponding memory update modules to augment the memory mechanism in transformers. [30] appends a set of learnable tokens
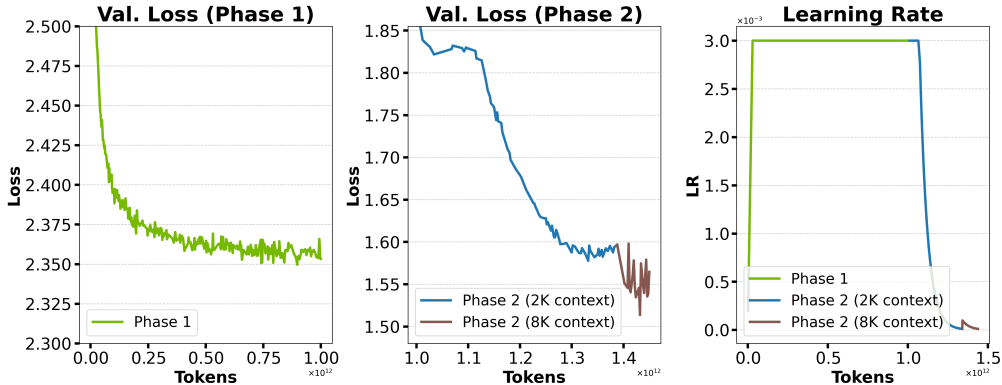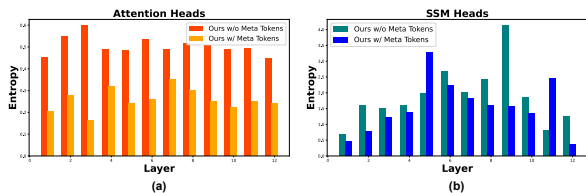
Figure 14 | Training curves of Hymba-1.5B.

Figure 15 | Visualize the layer-wise attention map entropy of (a) attention heads, and (b) SSM heads with and without meta tokens.

called registers to the image patches of vision transformers [89] to store global information and improve visual recognition. Our method combines ideas from all of these works in a more flexible manner. It optimizes the meta tokens jointly with model weights during the pretraining stage, is compatible with sliding window attention heads and other attention types or SSMs, and converts the meta tokens into KV-cache initialization during inference, without modifying the architecture.

Meta tokens reduce attention map entropy. We visualize the entropy of the attention map for both the attention and SSM heads [20, 16] before and after introducing meta tokens. As introduced in Sec. 2.3 of our main paper, the attention map entropy reflects the distribution of attention scores across tokens, where lower entropy indicates stronger retrieval effects [7], as the attention scores are concentrated around a smaller subset of tokens.

As shown in Fig. 15, we observe that after introducing meta tokens, both the attention and SSM heads exhibit an overall reduction in entropy. Specifically, entropy is significantly reduced in all attention heads and in 10 out of 12 layers of the SSM heads. This suggests that meta tokens can reduce attention map entropy, potentially helping both the attention and SSM heads focus more on a subset of important tokens that contribute most to task performance, as indicated by the boosted performance in Tab. 10.

E. Pretraining and Post-training Implementation Details

Pretraining settings. We train Hymba-125M/350M/1.5B models on 1.3T tokens, using a mix of DCLM-Baseline-1.0 [36], SmolLM-Corpus [37], and an internal high-quality dataset for 1T, 250B, and 50B tokens, respectively. We adopt the WSD learning rate scheduler [38] with three phases: (1) warmup steps set to 1% of the total steps, (2) a stable phase maintaining the peak learning rate of 3e-3, and (3) a decay phase reducing the learning rate to 1e-5 over 20% of the total steps, while gradually annealing to smaller, higher-quality datasets like SmolLM-Corpus and the internal dataset. We use a sequence length of 2K and a batch size of 2M tokens throughout the training process, which is conducted on 128 NVIDIA A100 GPUs. Details of Hymba-125M/350M/1.5B models are shown in Tab. 11.

We also show the training curves of Hymba-1.5B in Fig. 14.

Implementation details of post-training. We post-trained our 1.5B base model with a two-stage strategy: the first full-finetuning (FFT) stage and another direct preference optimization (DPO) [12] training. The learning rates are 5e-5, and 3e-6 for FFT and DPO, respectively. Both FFT and DPO training are carried out for one epoch with a cosine scheduler. The global batch size is set to 1024. To accelerate training, we follow the training recipe [61, 62, 63] to pack the samples and use a block size of 2048. We implement the finetuning and DPO training with the LMFlow toolkit [62]. In addition to full-finetuning, we also leverage Dora [13] to do parameter-efficient finetuning.

Baselines and downstream tasks. We compare Hymba-1.5B-Instruct with competitive lightweight instruction-tuned models, i.e., Llama-3.2-1B-Instruct [42], OpenELM-1-1B-Instruct [51],

Table 11 | Architecture details of Hymba models of different size.

Attribute	125M	350M	1.5B
Blocks	24	32	32
Hidden Size	512	768	1600
SSM State	16	16	16
Attn. Heads	8	12	25
Query Groups	4	4	5
Num. Full Attn	3	3	3
Window Size	1024	1024	1024
MLP Hidden	1664	2432	5504
Tie Embedding	True	True	True
Parameters	125M	350M	1.52B

Qwen2.5-1.5B-Instruct [64], and SmolLM-1.7B-Instruct [43]. We test the instruction-tuned models on MMLU (5-shot), IFEval, GSM8K (5-shot), GPQA (0-shot), and Berkeley Function-Calling Leaderboard v2 (BFCLv2) [65]. For BFCLv2, we use the official code from Gorilla project [65] and evaluate the BFCLv2-live category, including *live_simple*, *live_multiple*, *live_parallel*, *live_parallel_multiple*, *live_relevance*. We exclude *live_irrelevance*, since we found some baseline models without function calling abilities, could achieve high in the *live_irrelevance* category (where the model is not required to call function) and very low in other tasks, but still got high overall accuracy although these models are not helpful at all. For the remaining tasks, we directly use the lm-evaluation-harness [91].