

SwimBird: Eliciting Switchable Reasoning Mode in Hybrid Autoregressive MLLMs

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Abstract Multimodal Large Language Models (MLLMs) have made remarkable progress in multimodal perception and reasoning by bridging vision and language. However, most existing MLLMs perform reasoning primarily with textual CoT, which limits their effectiveness on vision-intensive tasks. Recent approaches inject a fixed number of continuous hidden states as “visual thoughts” into the reasoning process and improve visual performance, but often at the cost of degraded text-based logical reasoning. We argue that the core limitation lies in a rigid, pre-defined reasoning pattern that cannot adaptively choose the most suitable thinking modality for different user queries. We introduce SwimBird, a reasoning-switchable MLLM that dynamically switches among three reasoning modes conditioned on the input: (1) text-only reasoning, (2) vision-only reasoning (continuous hidden states as visual thoughts), and (3) interleaved vision–text reasoning. To enable this capability, we adopt a hybrid autoregressive formulation that unifies next-token prediction for textual thoughts with next-embedding prediction for visual thoughts, and design a systematic reasoning-mode curation strategy to construct SwimBird-SFT-92K, a diverse supervised fine-tuning dataset covering all three reasoning patterns. By enabling flexible, query-adaptive mode selection, SwimBird preserves strong textual logic while substantially improving performance on vision-dense tasks. Experiments across diverse benchmarks covering textual reasoning and challenging visual understanding demonstrate that SwimBird achieves state-of-the-art results and robust gains over prior fixed-pattern multimodal reasoning methods.

 **Project Page:** <https://accio-lab.github.io/SwimBird>

 **Github Repo:** <https://github.com/Accio-Lab/SwimBird>

 **HuggingFace:** <https://huggingface.co/datasets/Accio-Lab/SwimBird-SFT-92K>

1 Introduction

Building on the success of Chain-of-Thought (CoT) [32, 9] reasoning in LLMs, recent multimodal research has adopted step-by-step reasoning to decompose complex vision-and-language problems into intermediate steps that are easier to solve. With textual CoT, Multimodal Large Language Models (MLLMs) [44, 7, 16, 24] have significantly improved on tasks requiring symbolic manipulation, numerical calculation, and logical analysis.

However, this success does not fully transfer to vision-dense tasks where the bottleneck lies in dense perception and spatial reasoning rather than logical structure [4]. Typical examples include maze solving, fine-grained visual search, and other problems where accurate intermediate visual states are essential. On such tasks, purely textual CoT [19] can be an ill-posed interface: the model is forced to describe intermediate visual evidence in language even when language is not a faithful carrier, causing brittle reasoning and error accumulation [37]. To address this, recent works introduce latent visual reasoning [11, 22] that supervises models to generate semantically grounded continuous

Case 1: Perimeter of a Rectangle

Question: What is the perimeter of the rectangle?

Correct Answer: 6

The rectangle has:
 - Two sides of length 1 yard
 - Two sides of length 2 yards

The perimeter is the total distance around the shape.

Perimeter = $1 \text{ yd} + 2 \text{ yd} + 1 \text{ yd} + 2 \text{ yd}$
 Perimeter = $(1 + 2 + 1 + 2) \text{ yd}$
 Perimeter = 6 yd

The perimeter of the rectangle is 6 yards. ✓

Textual CoT Method

Unified CoT Method

Latent Visual CoT Method

SwimBird (Switchable Reasoning Mode)

Case 2: Maze Pathfinding

Quantify the relocation steps between green and red positions

Correct Answer: 4

The path is as follows:
 - From the green square, move right to the red square.

There is only one step involved in this movement.

Therefore, the number of relocation steps between the green and red positions is *1**. X

Modality Mismatch

Textual CoT Method

Unified CoT Method

Latent Visual CoT Method

SwimBird (Switchable Reasoning Mode)

Case 3: Room Object Identification

What object is situated in the corner of the room depicted in this image?

Answer: Television

Based on the image provided, the object situated in the corner of the room is an **air conditioner**. X

Textual CoT Method

Latent Visual CoT Method

Unified CoT Method

Latent Visual CoT Method

SwimBird (Switchable Reasoning Mode)

Figure 1: SwimBird enables query-adaptive multimodal reasoning by dynamically switching among text-only, vision-only, and interleaved vision-text modes. As illustrated, it avoids redundant latent steps on text-centric queries (Case 1), relies on latent visual thoughts for vision-dense spatial problems (Case 2), and interleaves visual grounding with textual deduction when both are needed (Case 3), mitigating modality mismatch and improving robustness.

hidden states as visual thoughts, enabling intermediate visual representations to be maintained and updated across steps, which substantially strengthens performance on vision-dense benchmarks.

Despite these advances, existing multimodal CoT designs largely rely on a rigid, pre-defined reasoning pattern. Concretely, prior methods [25, 39, 36] typically fall into three fixed paradigms: text-only CoT, vision-only CoT, or interleaved vision–text CoT. As shown in Fig. 1, such fixed patterns create a mismatch between the reasoning modality and the actual needs of the question: forcing visual thoughts for text-centric queries can interfere with discrete symbolic reasoning, while restricting strongly visual queries to text-only reasoning removes an appropriate latent workspace. Even interleaved reasoning remains a fixed schedule that may generate redundant modality steps [23].

We argue that the core limitation is the assumption that a single, static reasoning template can generalize across heterogeneous multimodal queries. Different questions demand different internal computation formats. Some require only discrete symbolic steps, some require only latent visual transitions, and some require tight alternation between visual grounding and textual deduction. A **more capable MLLM should therefore be able to choose when to think in language, when to think in vision, conditioned on the input and the evolving reasoning state**.

Motivated by this, we propose **SwimBird**, a reasoning-switchable MLLM for query-adaptive multimodal reasoning. SwimBird is built on two key ideas derived from the limitations above. First, we adopt a hybrid autoregressive formulation that supports both (i) standard next-token prediction for textual thoughts and (ii) next-embedding prediction for continuous visual thoughts. This unified generation interface provides the foundation for switchable reasoning. Second, we attribute the rigidity of prior patterns partly to training data bias. We therefore design a systematic curation strategy that filters and categorizes multimodal CoT samples into reasoning modes based on their visual dependency and reasoning characteristics. Through this strategy, we construct **SwimBird-SFT-92K**, a diverse supervised fine-tuning dataset covering text-only, vision-only, and interleaved vision–text patterns. With these designs, SwimBird can dynamically switch among three reasoning modes.

Importantly, `SwimBird` also removes the fixed-budget constraint in visual reasoning. Instead of generating a constant-length sequence of visual thought tokens, it dynamically determines the number of visual thought tokens during vision-only or interleaved reasoning, allocating more latent computation to vision-dense queries while avoiding redundant visual thoughts for text-centric problems. As a result, a single model can robustly handle diverse query types, whereas fixed-pattern baselines typically excel only on a subset and may underperform when the required thinking modality or visual-thought budget deviates from their pre-defined design.

Our contributions are summarized as follows:

- We identify two key bottlenecks of prior multimodal CoT frameworks, namely fixed reasoning-mode templates and fixed visual-thought lengths, and show how they lead to a modality mismatch that harms either vision-dense performance or text-based logical reasoning.
- We introduce `SwimBird`, a hybrid autoregressive MLLM that can dynamically switch among text-only, vision-only, and interleaved reasoning modes, combining next-token prediction for textual thoughts with next-embedding prediction for visual thoughts.
- We further introduce adaptive visual-thought allocation, enabling `SwimBird` to dynamically determine the number of continuous visual-thought tokens based on query complexity.
- We design a systematic reasoning-mode curation strategy for multimodal CoT samples and construct `SwimBird-SFT-92K`, a dataset covering three reasoning patterns that enables query-adaptive mode selection.
- Extensive experiments across diverse benchmarks demonstrate that `SwimBird` achieves state-of-the-art performance on both text-centric reasoning and challenging vision-dense tasks, outperforming prior fixed-pattern multimodal reasoning methods.

2 Related Works

2.1 Textual CoT in MLLMs

The integration of vision and language has evolved from discriminative tasks toward generative reasoning frameworks. Early MLLMs focus primarily on visual question answering through direct answer generation [13, 15, 27, 14, 35]. With the success of step-by-step reasoning in LLMs, recent MLLMs incorporate explicit reasoning chains to handle complex multimodal problems [1, 29, 34]. These models generate intermediate textual explanations before producing final answers, demonstrating improved performance on mathematical word problems, scientific diagram understanding, and multi-hop visual reasoning [38, 31, 17]. Despite their effectiveness on logic-heavy benchmarks, these text-based reasoning approaches struggle when the core challenge lies in visual perception rather than logical decomposition [20]. Tasks requiring spatial transformation tracking, visual state prediction, or fine-grained visual comparison expose the fundamental limitation that the model is forced to describe intermediate visual evidence in language, even when language is not a faithful or efficient carrier for the required information, leading to brittle reasoning and error accumulation.

2.2 Latent Visual Reasoning

Recognizing the constraints of language-only reasoning, researchers have explored alternative computational substrates for visual thinking [18, 28]. Recent methods propose latent visual reasoning by training models to produce continuous embeddings supervised by visual reconstruction objectives. For instance, `Mirage` [36] employs hidden states trained to approximate annotated helper images, while `LVR` [11] focuses on reconstructing cropped image regions. `SkiLa` [22] proposes unified reasoning that alternates between generating latent visual tokens and discrete textual tokens. However, existing latent reasoning methods uniformly apply the same reasoning structure across all inputs: models trained with visual thoughts always generate them, even for purely textual queries. Furthermore, these methods use fixed-length latent tokens regardless of whether a problem requires minimal or extensive visual deliberation. `SwimBird` addresses both limitations through dynamic mode selection and adaptive visual token budgets, enabling truly query-adaptive multimodal reasoning.

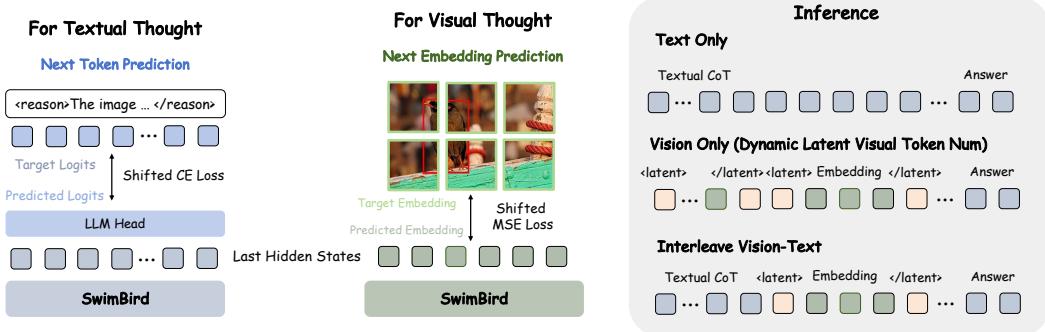


Figure 2: *SwimBird adopts a hybrid autoregressive formulation that performs next-token prediction for textual thoughts and switches to next-embedding prediction for visual thoughts. During inference, *SwimBird* performs query-adaptive multimodal reasoning by dynamically selecting among three modes conditioned on the input: text-only, vision-only, and interleaved vision-text reasoning.*

3 Method

SwimBird adopts a hybrid autoregressive formulation that supports both discrete textual tokens and continuous latent visual tokens. As shown in Fig. 2 (left), it performs standard next-token prediction for textual thoughts, optimized with a shifted cross-entropy loss, and performs next-embedding prediction for visual thoughts, optimized with a MSE loss to reconstruct the embeddings of intermediate thinking images. During inference (Fig. 2 right), *SwimBird* performs query-adaptive reasoning by generating either (i) text-only traces, (ii) vision-only traces with a variable-length latent span, or (iii) interleaved vision–text traces, conditioned on the input.

3.1 Hybrid Autoregressive Modeling

Textual thought as next-token prediction. For textual reasoning spans, *SwimBird* behaves like a standard language model. Given a token sequence $\{w_1, \dots, w_T\}$, the model outputs logits parameterizing

$$p_\theta(w_t | w_{<t}, \mathbf{x}), \quad (1)$$

where \mathbf{x} denotes the observed image (and prior context). We train these spans with the standard cross-entropy loss:

$$\mathcal{L}_{\text{text}} = - \sum_{t=1}^T \log p_\theta(w_t | w_{<t}, \mathbf{x}). \quad (2)$$

This objective preserves the discrete symbolic manipulation and logical consistency of the language backbone, which is essential for text-centric reasoning tasks.

Visual thought as next-embedding prediction. For vision-only reasoning or visual segments inside interleaved reasoning, *SwimBird* generates a sequence of continuous latent tokens (visual thoughts) $\{\mathbf{z}_1, \dots, \mathbf{z}_K\}$, each represented as a hidden-state embedding rather than a discrete word. Concretely, we treat each visual-thought step as predicting the next embedding in an autoregressive manner:

$$\hat{\mathbf{z}}_k = f_\theta(\mathbf{z}_{<k}, w_{\leq T}, \mathbf{x}), \quad (3)$$

and supervise it with a shifted mean squared error (MSE) loss against target embeddings \mathbf{z}_k :

$$\mathcal{L}_{\text{vis}} = \sum_{k=1}^K \|\hat{\mathbf{z}}_k - \mathbf{z}_k\|_2^2. \quad (4)$$

Here, the target embeddings are computed by encoding the intermediate thinking images with the same vision encoder (and projection) used by *SwimBird*, thus grounding latent visual thoughts in semantically meaningful visual states.

Unified training objective. A training instance may contain pure textual CoT, pure visual CoT, or interleaved segments. We optimize a unified objective that sums modality-specific losses over the activated segments:

$$\mathcal{L} = \lambda_{\text{text}} \mathcal{L}_{\text{text}} + \lambda_{\text{vis}} \mathcal{L}_{\text{vis}}, \quad (5)$$

Data Source	All Mode	Text Only	Vision Only	Interleave	Problem Domain
Zebra-CoT	26.3K	0	5.9K	20.4K	Visual Search, Jigsaw, Maze, Geometry, Chess...
ThinkMorph	7.1K	0	1.2K	5.9K	Visual Search, Spatial Navigation, Jigsaw, Chart
MathCanvas	8.9K	0	1.7K	7.2K	Geometry, Algebra, Calculus, Statistics
OpenMMReasoner	50K	50K	0	0	General VQA, Math VQA, Text QA
Total	92.3K	50K	8.8K	33.5K	

Table 1: Detailed statistics of *SwimBird-SFT-92K*.

where λ_{text} and λ_{vis} are balancing coefficients. In practice, each sample only contributes to the losses of the modes it contains, enabling the model to learn all three reasoning patterns without forcing unnecessary supervision.

Mode switching with special delimiters To enable controllable and learnable switching among reasoning modes, we introduce explicit delimiters in the target sequences. Specifically, we mark visual-thought spans using special tokens such as `<|latent_start|>` and `<|latent_end|>`. During training, these delimiters define where the model should produce continuous latent embeddings instead of textual tokens. During inference, *SwimBird* generates these delimiters autoregressively, which makes mode selection *query-adaptive*: the model can decide whether to enter a latent visual-thinking phase, remain in text-only reasoning, or alternate between the two (Fig. 2 right).

3.2 Dynamic Latent Token Budget

Prior latent visual reasoning methods typically adopt a fixed number of latent tokens (or a fixed pooling strategy) for all inputs. This design has two drawbacks: (1) it can lead to insufficient capacity for vision-dense, high-resolution images, while wasting computation on vision-easy, low-resolution images; (2) pooling intermediate process images into a fixed token length during training may discard spatial details, making it harder for the model to learn semantically meaningful latent embeddings.

As shown in Figure 3, *SwimBird* addresses these issues with a resolution-aware, dynamic latent token budget. Benefiting from the naive-resolution property of the Qwen ViT, we assign different maximum pixel budgets to the question image and the intermediate thinking images during training, which directly controls the maximum number of visual tokens produced by the vision encoder for each type of image. Concretely, we allow the vision encoder to output a variable number of visual tokens according to image resolution, bounded by an independent range $[N_{\min}, N_{\max}]$ (implemented via pixel/patch budget control). This avoids aggressive pooling that discards fine-grained evidence, while preventing excessively long visual sequences from dominating computation. Consequently, *SwimBird* can preserve detailed visual information when needed (e.g., tiny targets or dense diagrams) and remain efficient on simpler cases.

With this resolution-aware training setup, *SwimBird* further learns to allocate latent computation dynamically at inference time. In vision-only and interleaved modes, the number of latent tokens K is not pre-defined: the model keeps generating latent embeddings until it decides to stop by emitting `</latent>`. This variable-length latent span naturally matches the amount of visual thinking to the perceived difficulty of the query.

3.3 Switchable Reasoning SFT Dataset Construction

To enable switchable reasoning modes, we curate a diverse SFT dataset covering three reasoning patterns: (1) text-only CoT, (2) vision-only CoT where intermediate images are sufficient, and (3) interleaved vision-text CoT requiring both modalities. Our curation pipeline consists of three stages:

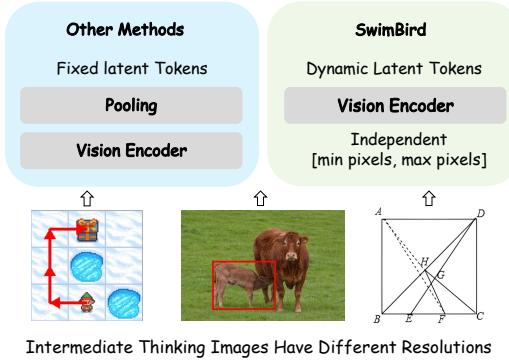


Figure 3: Resolution-aware, dynamic latent tokens budget.

Model	V* Bench	HR-Bench 4K	HR-Bench 8K	MME RealWorld	Avg.
<i>Textual Reasoning Models</i>					
GPT-4o [8]	66.0	59.0	55.5	62.8	60.9
GPT-5-mini	63.9	66.3	60.9	-	-
Qwen2.5-VL-32B-Instruct	80.6	69.3	63.6	59.1	68.2
Qwen2.5-VL-7B-Instruct	75.3	65.5	62.1	56.8	64.9
Qwen3-VL-8B-Instruct *	83.8	76.5	71.3	61.9	73.4
Qwen3-VL-8B-Thinking	77.5	72.4	68.1	-	-
InternVL3-8B [46]	81.2	70.0	69.3	-	-
LLaVA-OneVision [12]	75.4	63.0	59.8	57.4	63.9
Vision-R1 [7]	80.1	64.8	57.0	-	-
<i>Latent Visual Reasoning Models</i>					
Monet [28]	83.3	71.0	68.0	-	-
LVR [11]	81.7	69.6	66.1	-	-
SkiLa [22]	84.3	72.0	66.5	-	-
<i>Multimodal Agentic Models</i>					
SEAL [33]	74.8	-	-	-	-
Pixel Reasoner [26]	84.3	72.6	66.1	64.4	71.9
DeepEyes [45]	83.3	73.2	69.5	64.1	72.5
Thyme [42]	82.2	77.0	72.0	64.8	74.0
DeepEyesV2 [6]	81.8	77.9	73.8	64.9	74.6
SwimBird	85.5	79.0	74.9	65.3	76.2

Table 2: Performance on fine-grained visual understanding benchmarks. Here, * denotes the results are reproduced by ourselves.

Stage 1: Candidate collection and easy-instance filtering. We collect raw image-text interleaved CoT data from ThinkMorph [5], Zebra-CoT [10], and MathCanvas-Instruct [21]. These datasets provide multimodal reasoning chains with intermediate visual thinking steps. where each sample contains intermediate thinking images. To focus on cases where intermediate visual reasoning is useful, we remove instances that are already solvable from the original input: Qwen3VL-8B is evaluated on the question and the original image, and correctly answered samples are filtered out.

Stage 2: Reasoning-mode labeling via pass@8. For each remaining sample, we compute two pass@8 scores with Qwen3VL-8B: $\text{pass}_{\text{base}}$ using only the question and problem image, and $\text{pass}_{\text{hint}}$ additionally providing the intermediate thinking images as visual hints. We judge each sampled answer using Qwen3-235B-Instruct given the question, prediction, and ground truth. We keep samples with $\text{pass}_{\text{hint}} \geq \text{pass}_{\text{base}}$, indicating that intermediate thinking images provide non-negative gains. Among them, we label samples with $\text{pass}_{\text{hint}} \geq 0.75$ as vision-only, since the model can solve the problem with high probability using the intermediate thinking images without an explicit textual CoT. The remaining kept samples, where $\text{pass}_{\text{hint}} \geq \text{pass}_{\text{base}}$ but $\text{pass}_{\text{hint}} < 0.75$, are labeled as interleaved vision–text, since the images help but are insufficient for consistently correct solutions and textual reasoning is still needed. This procedure yields 42K high-quality SFT samples covering the vision-only and interleaved modes.

Stage 3: Add text-only CoT data. To complete the three-mode training set, we sample 50K text-only CoT instances from OpenMMReasoner [40], which provides pass@8-filtered textual CoT traces. Combining them with the 42K samples from Stage 2 yields **SwimBird-SFT-92K**, covering text-only, vision-only, and interleaved vision–text patterns. Detailed statistics are reported in Table 1.

4 Experiments

Training Details We adopt Qwen3-VL 8B [1] as the base model and conduct supervised fine-tuning on our curated SwimBird-SFT-92K. Training is performed on A100-80G GPUs with a global batch size of 128. The vision encoder and multimodal projector are kept frozen, and only the LLM parameters are updated. A cosine learning rate scheduler is applied with an initial learning rate of 1e-5.

Models	General VQA		Multimodal Reasoning		
	MMStar	RealWorldQA	WeMath	DynaMath	MathVerse_MINI
Qwen2.5-VL-32B-Instruct	70.3	-	-	-	48.5
Qwen2.5-VL-7B-Instruct	60.3	67.4	34.6	53.3	45.6
Qwen3-VL-8B-Instruct *	64.7	71.8	38.8	65.3	61.3
LLaVA-OneVision [12]	61.9	69.9	20.9	-	19.3
DeepEyes [45]	-	-	38.9	55.0	47.3
DeepEyesV2 [6]	-	-	38.1	57.2	52.7
SkiLa [22]	64.8	69.3	-	-	-
SwimBird	71.2	73.1	49.5	67.2	65.8

Table 3: Performance on general vqa and multimodal reasoning tasks. Here, * denotes the results are reproduced by ourselves.

Baselines and Benchmarks To comprehensively assess the effectiveness of **SwimBird**, we compare it against three categories of baselines: (1) textual reasoning models, including advanced closed-source systems (e.g., GPT-4o and GPT-5-mini) and state-of-the-art open-source models (e.g., Qwen2.5/3-VL, LLaVA-OneVision); (2) latent visual reasoning models (e.g., Monet, LVR, SkiLa); and (3) multimodal agentic models that rely on explicit tool/workflow designs (e.g., Pixel Reasoner, DeepEyes, Thyme). We evaluate on two groups of benchmarks: (i) fine-grained/high-resolution visual understanding (V* Bench [33], HR-Bench 4K/8K [30], MME-RealWorld [43]; Table 2), and (ii) general VQA and multimodal reasoning (MMStar [2], RealWorldQA [3], WeMath [17], DynaMath [47], MathVerse_MINI [41]; Table 3). Results marked with * are reproduced by ourselves.

4.1 Main Results

Fine-grained Visual Understanding Table 2 demonstrates that **SwimBird** achieves state-of-the-art performance on fine-grained and high-resolution perception. **SwimBird** obtains 85.5 on V* Bench, 79.0 on HR-Bench 4K, and 74.9 on HR-Bench 8K, outperforming strong textual reasoning baselines such as Qwen3-VL-8B-Instruct (83.8/76.5/71.3). Notably, Qwen3-VL-Thinking performs worse than Qwen3-VL-Instruct on visual perception, further supporting our claim that a mismatched reasoning mode can harm performance. Furthermore, **SwimBird** also outperforms current state-of-the-art multimodal agentic models such as Thyme (82.2/77.0/72.0) and DeepEyesV2 (81.8/77.9/73.8), which enhance perception via explicit cropping tools, highlighting that **SwimBird** can achieve stronger fine-grained perception without relying on complex tool pipelines. We attribute these gains to **SwimBird**'s query-adaptive reasoning mode switching and adaptive latent-token allocation. Fine-grained visual tasks often require precise spatial evidence that is difficult to faithfully compress into text; meanwhile, forcing latent visual thoughts on text-centric steps can be redundant. By switching to vision-only reasoning when dense perception is needed (and allocating more latent computation for high-resolution inputs), **SwimBird** better preserves visual details and reduces modality mismatch, leading to consistently higher accuracy.

General VQA and Multimodal Reasoning Beyond perception, **SwimBird** also shows strong improvements on general VQA and reasoning-heavy benchmarks. As shown in Table 3, **SwimBird** reaches 71.2 on MMStar and 73.1 on RealWorldQA, exceeding Qwen3-VL-8B-Instruct* (64.7/71.8) and even outperforming Qwen2.5-VL-32B-Instruct on MMStar. More importantly, **SwimBird** delivers clear gains on multimodal reasoning: 49.5 on WeMath, 67.2 on DynaMath, and 65.8 on MathVerse_MINI, outperforming strong open-source methods and agentic models. These results suggest that **SwimBird**'s latent visual thoughts do not come at the cost of symbolic reasoning. Instead, **SwimBird** stays in text-only reasoning when the task is primarily linguistic or mathematical, and invokes vision-only or interleaved latent thinking only when additional visual evidence is beneficial. Learned from the multi-pattern supervision in **SwimBird-SFT-92K**, this query-adaptive selection avoids redundant visual thoughts that could interfere with textual logic, while still leveraging latent visual computation for vision-dependent subproblems.

Latent Tokens	HRBench4K	HRBench8K	RealWorldQA
16	76.4	71.4	73.1
32	79.0	74.9	73.1
64	77.8	73.4	72.7
128	76.0	71.8	72.7

Table 4: Impact of maximum latent tokens budget.

MSE Weight	HRBench4K	HRBench8K	RealWorldQA
0.1	79.0	71.8	72.8
0.2	79.0	74.9	73.1
0.5	77.8	75.9	72.0
1.0	79.4	73.8	71.9

Table 5: Impact of MSE loss weight coefficients.

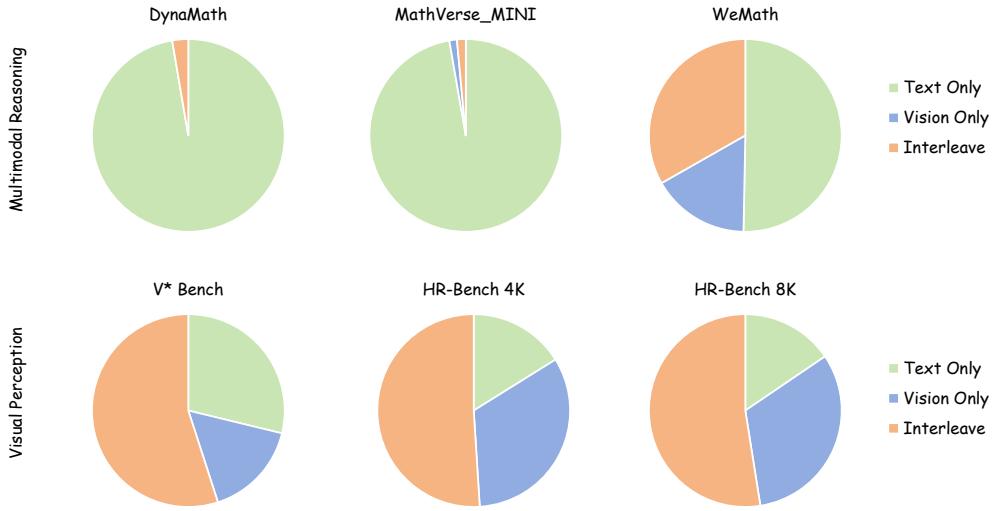
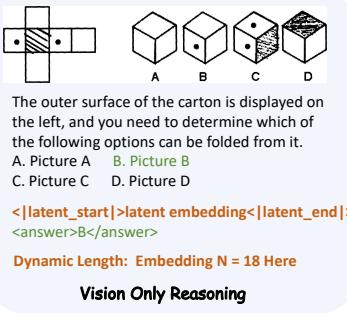


Figure 4: Distribution of reasoning mode across different benchmarks for *SwimBird*.

4.2 Ablation Studies

Impact of the Maximum Latent Token Budget. We study how the maximum latent token budget N_{\max} influences performance under our dynamic range setting $[N_{\min}, N_{\max}]$. We fix $N_{\min} = 2$ to ensure small images can be encoded without losing effective resolution, and vary $N_{\max} \in \{16, 32, 64, 128\}$. As shown in Table 4, increasing N_{\max} from 16 to 32 yields clear gains on vision-dense benchmarks (HRBench4K: 76.4 vs. 79.0; HRBench8K: 71.4 vs. 74.9), indicating that a moderate upper bound provides sufficient capacity for high-resolution perception. However, further expanding N_{\max} to 64 or 128 does not help and even degrades performance (e.g., HRBench8K: 74.9 vs. 73.4 vs. 71.8), while RealWorldQA slightly drops (73.1 vs. 72.7). This suggests that an overly large latent budget may introduce redundant visual computation and interfere with overall reasoning. Overall, $N_{\max} = 32$ offers the best trade-off and is used as the default setting.

Impact of the MSE Loss Weight Coefficient. We ablate the weight of the visual-thought reconstruction loss by varying λ_{vis} while keeping other settings fixed. As shown in Table 5, a moderate MSE weight yields the most balanced performance. Specifically, setting $\lambda_{\text{vis}} = 0.2$ achieves strong results across all benchmarks. When λ_{vis} is too small (0.1), the supervision on latent visual thoughts becomes weak, leading to a notable drop on the most vision-dense benchmark (HRBench8K: 71.8). In contrast, increasing λ_{vis} to 0.5 improves HRBench8K (75.9) but degrades RealWorldQA (72.0), suggesting that overly emphasizing MSE training may bias the model toward visual reconstruction at the expense of general multimodal reasoning. With $\lambda_{\text{vis}} = 1.0$, HRBench4K slightly increases (79.4) but performance drops on HRBench8K and RealWorldQA, indicating instability under overly strong visual-loss weighting. Overall, we use $\lambda_{\text{vis}} = 0.2$ as the default, which best balances visual reasoning and text-centric reasoning.



Vision Only Reasoning

■ + 66 = 33 + 60

Find the value of the black square.

Answer: 27

<reason>We are given the equation: $\square + 66 = 33 + 60$

First, compute the right-hand side: $33 + 60 = 93$

So the equation becomes: $\square + 66 = 93$

Now subtract 66 from both sides to solve for \square :

$$\square = 93 - 66$$

$$\square = 27$$

Therefore, the value of the black square is 27.</reason>
<answer>27</answer>

Text Only Reasoning



Interleave Vision-Text Reasoning

Figure 5: Analysis of Different Reasoning-Mode Case.

4.3 Analysis of Switchable Reasoning Mode

Analysis of Reasoning-Mode Distribution We analyze the distribution of SwimBird’s reasoning modes across benchmarks (Fig. 4) to verify its query-adaptive behavior. Overall, the selected mode matches each benchmark’s dominant difficulty. On **text-logic-dominant** multimodal reasoning datasets (DynaMath and MathVerse_MINI), SwimBird almost always uses text-only reasoning, with vision-only and interleaved traces rarely triggered, suggesting it avoids redundant latent visual thoughts when symbolic manipulation and linguistic deduction are sufficient. On **vision-dense perception** benchmarks (V* Bench and HR-Bench 4K/8K), SwimBird frequently activates vision-only and especially interleaved vision–text reasoning, reflecting the need to alternate between visual grounding (e.g., tiny targets in high-resolution images) and explicit textual deduction. The proportion of vision-only reasoning increases from HR-Bench 4K to 8K, consistent with higher perceptual load at higher resolutions. WeMath exhibits a more **balanced** mixture of all three modes, where some problems are text-centric while others require substantial visual grounding. These results confirm that SwimBird does not follow a fixed template, but instead selects reasoning modes in an instance-dependent manner to mitigate modality mismatch.

Analysis of Different Reasoning-Mode Cases Fig. 5 provides qualitative examples of SwimBird’s mode selection. For vision-only reasoning (top-left), the cube-net folding problem mainly requires spatial perception and mental rotation; SwimBird directly enters a latent visual-thought span and outputs the answer without unnecessary textual CoT, while allocating an appropriate latent length (e.g., $N=18$). For text-only reasoning (top-right), the arithmetic equation is purely symbolic; SwimBird solves it with textual deduction, avoiding redundant visual thoughts that could interfere with logical steps. For interleaved vision–text reasoning (bottom), reading a phone number from a small region in a natural image requires both precise visual localization and explicit option comparison; SwimBird first uses latent visual thoughts to focus on the relevant region, then switches back to text for verification and decision making, again with a dynamically allocated latent length (e.g., $N=24$). Together, these cases show that SwimBird mitigates modality mismatch by choosing when to think in vision versus language and by adaptively allocating visual-thought computation to match perceptual difficulty.

5 Prompt

To guide **SwimBird**'s query-adaptive reasoning mode selection, we design a system prompt that explicitly instructs the model on how to switch between textual and visual thinking modes. As shown in Figure 6, the prompt defines three reasoning patterns: text-only, vision-only, and interleaved, using structured tags (<reason> for textual thoughts and <latent> for visual thoughts), and allows the model to dynamically choose the most appropriate mode or combination based on the input query.

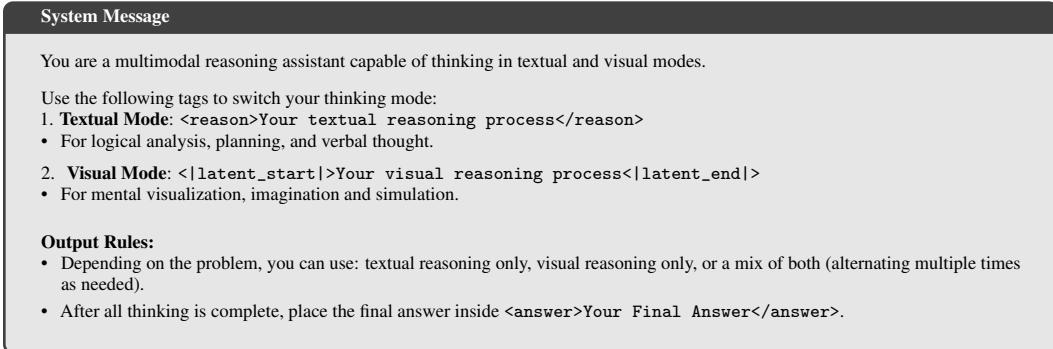


Figure 6: System prompt used for *SwimBird*.

6 Conclusion

We present **SwimBird**, a reasoning-switchable MLLM that addresses the fixed reasoning pattern in prior multimodal CoT frameworks. **SwimBird** adopts a hybrid autoregressive paradigm and can adaptively switch among text-only, vision-only, and interleaved vision-text reasoning, while dynamically allocating the latent visual token budget. We also construct **SwimBird-SFT-92K** with a systematic curation and mode-labeling strategy to enable effective multi-mode training. Extensive experiments show that **SwimBird** achieves SOTA performance on both text-centric reasoning and challenging vision-dense tasks.

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