ZEBRA-COT: A DATASET FOR INTERLEAVED VISION-LANGUAGE REASONING

Anonymous authors
Paper under double-blind review

ABSTRACT

Humans often rely on visual aids, such as diagrams or sketches, when tackling complex problems. Teaching multimodal models to adopt similar strategies, a process known as Visual Chain of Thought (visual CoT), is much more difficult. The main challenges are: (1) weak performance of off-the-shelf visual CoT, which hinders reinforcement learning, and (2) the lack of high-quality visual CoT training data. We introduce **ZEBRA-COT**, a diverse large-scale interleaved text–image reasoning dataset with 182,384 reasoning traces across 18 domains with over 50 distinct tasks. This dataset is specifically designed to train models to natively perform visual CoT. We emphasize four categories of tasks where sketching or visual reasoning is especially natural, spanning (a) *scientific questions* such as geometry, physics, and algorithms; (b) *2D visual reasoning tasks* like visual search and jigsaw puzzles; (c) *3D reasoning tasks* including 3D multi-hop inference, embodied and robot planning; and (d) *visual logic problems and strategic games* like chess. Fine-tuning Anole-7B model on ZEBRA-COT yields a +12% improvement in our test-set accuracy and up to +13% performance gains on standard VLM benchmarks. Similarly, fine-tuning Bagel-7B produces models capable of generating high-quality interleaved visual reasoning chains, underscoring ZEBRA-COT's effectiveness in advancing multimodal reasoning.

1 INTRODUCTION

Human cognition naturally integrates multimodal thought processes when solving complex problems. For example, a high school student sketches diagrams to solve geometry or physics problems, an engineer creates diagrams to design and debug workflows, and a data scientist generates plots to better understand data. These visual aids are central to effective problem solving. While recent vision-language models (VLMs) have shown strong performance on multimodal tasks like visual question answering, their reasoning traces remain predominantly textual. Enabling models to explicitly reason in the visual space, Visual Chain of Thought (visual CoT), remains a fundamental open challenge. Unlocking visual CoT may improve reasoning performance in domains where visual intuition is relevant and may make the reasoning patterns expressed by models more interpretable to humans.

Recent advances in frontier multimodal models (Team et al., 2023; Hurst et al., 2024; Bai et al., 2025; OpenAI, 2025a; Team, 2024; Chern et al., 2024; Sun et al., 2024; Deng et al., 2025) have made visual CoT feasible primarily through agentic pipelines that leverage external tools (*e.g.*, Python functions, or expert vision models) for visual programming (Surís et al., 2023), such as generating sketches for geometry, algorithms, and spatial reasoning tasks (Hu et al., 2024; OpenAI, 2025b), or bounding boxes for fine-grained visual tasks (Shao et al., 2024a; Wu and Xie, 2024; Zheng et al., 2025). An emerging possibility is innate visual reasoning, where models directly generate explicit visual tokens during their thinking process (Li et al., 2025; Chern et al., 2025; Xu et al., 2025b). However, current VLMs with interleaved text and image generation capabilities (Team, 2024; Chern et al., 2024) either fail to generate useful visual aids for reasoning or are not inherently trained for such multimodal generation during the reasoning process (Deng et al., 2025), making reinforcement learning approaches to reasoning infeasible. Li et al. (2025) demonstrate visual CoT in synthetic mazes by training specialist models, but we remain far from foundation models capable of general high-quality visual CoT, largely due to the lack of large-scale diverse interleaved text and image reasoning training datasets.

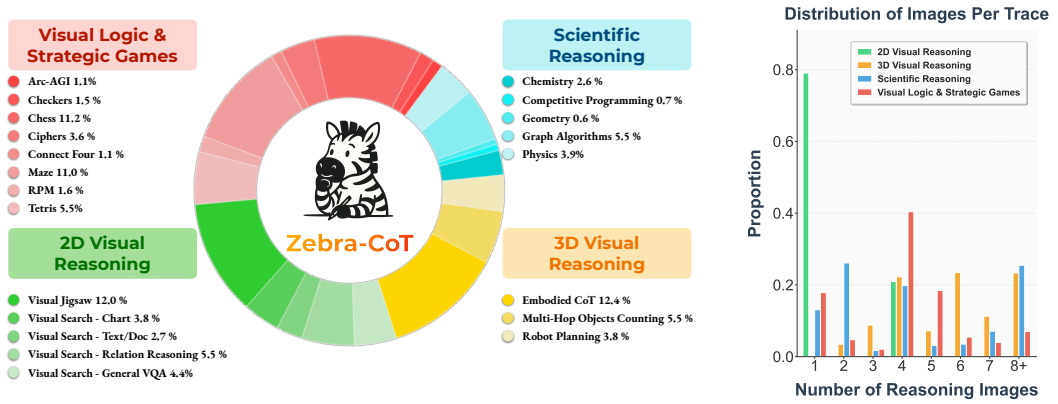


Figure 1: We curate a large-scale multimodal dataset by sourcing and cleaning raw traces from real-world domains, and generating synthetic examples using templated reasoning filled in by VLMs. ZEBRA-COT comprises 4 major categories and 18 subcategories, encompassing over **182K** instances in total. A detailed breakdown of the data statistics appears in Table 3.

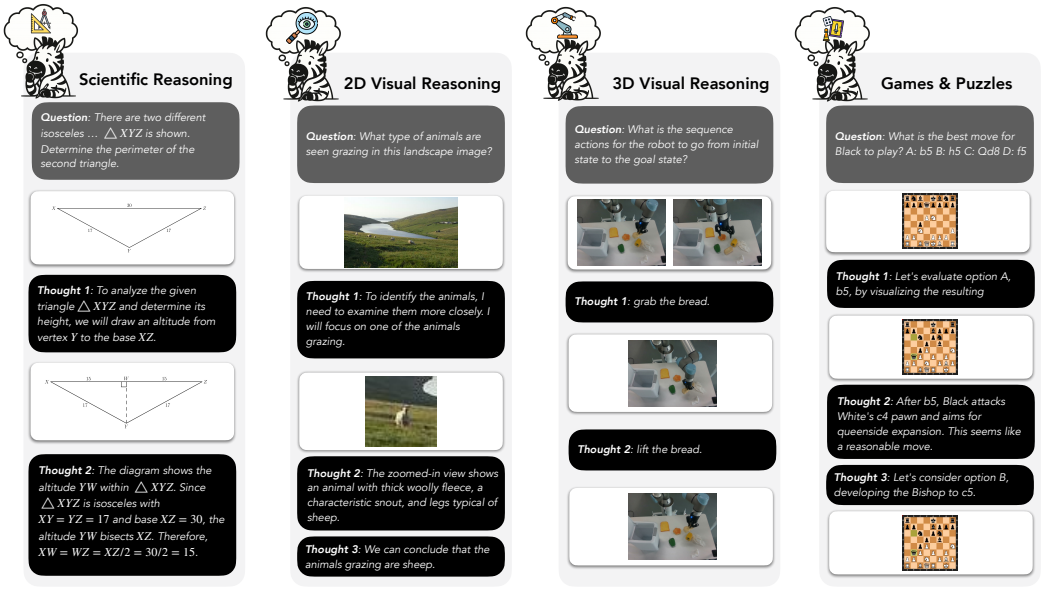


Figure 2: Visual CoT helps answer complex visual reasoning questions, as illustrated by examples from ZEBRA-COT.

To support the development of next generation vision language models that can explicitly reason with both text and visual modalities, we present **ZEBRA-COT**, a high quality dataset of interleaved text and image reasoning traces. Our dataset covers four main categories: scientific questions, 2D visual reasoning, 3D visual reasoning, and visual logic and strategic games, each containing multiple subdomains and task types, as exemplified in Figure 2. To the best of our knowledge, ZEBRA-COT is the first dataset to provide diverse and logically coherent multimodal reasoning traces across such a wide range of domains. Unlike prior large-scale interleaved datasets that are primarily composed of web-scraped image-text pairs with weak semantic alignment and no explicit reasoning structure (Li et al., 2024b; Awadalla et al., 2024; Zhu et al., 2023), ZEBRA-COT is carefully curated as a training resource in the spirit of high-quality text-based reasoning datasets. At the same time, compared to the only existing open-source interleaved text visual reasoning dataset we are aware of, VISUAL-COT (Shao et al., 2024a), which focuses on a single task of visual search, ZEBRA-COT introduces a much broader and more diverse set of tasks with richer reasoning trajectories. We provide a detailed comparison with other datasets below in Table 1.

Dataset	Primary Task	CoT Modality	Suitability for visual CoT Training
GQA	Compositional visual QA	Text	No visual CoT
ScienceQA	Multimodal science QA	Text	No visual CoT
CLEVR	Synthetic compositional visual QA	Text	No visual CoT
VCR	Visual commonsense QA with rationale	Text	No visual CoT
VideoCoT	Video QA	Text	No visual CoT
EgoCOT	Embodied planning	Text	No visual CoT
LLaVA-CoT	Multimodal reasoning QA	Text	No visual CoT
MAmmoTH-VL	Large scale multimodal instruction tuning	Text	No visual CoT
MM-Verify	Multimodal reasoning with verification	Text	No visual CoT
R1-Onevision	A SFT and RL multimodal reasoning dataset	Text	No visual CoT
Visual CoT	Visual-search QA with bbox CoT	Image, Text	Limited to visual search tasks
MM-PhyQA	Physics visual CoT	Image, Text	Physics data only, not open sourced
CoT VLA	Robotics visual CoT	Image, Action	No text reasoning
OmniCorpus	10 B-level interleaved corpus	None	Noisy pretraining data without CoT
MINT-1T	1 T-token web-scale interleaved data	None	Noisy pretraining data without CoT
ZEBRA-COT	Diverse and high quality visual CoT	Image, Text	Diverse interleaved vision–language CoT

Table 1: ZEBRA-COT introduces a broader set of high quality visual CoT traces compared with prior datasets and pipelines.

Our contributions are summarized as follows:

1. We release ZEBRA-COT, a high quality and diverse dataset with interleaved text and visual CoT that contains 182,384 samples for training models to natively perform visual CoT for problem solving. Details regarding the dataset are shown in Section 3
2. We evaluate three frontier LLMs, including GPT-5, Claude Sonnet 4, and Gemini 2.5 Pro, on the tasks in ZEBRA-COT in Section 4. Despite their advanced multimodal reasoning capabilities, these models perform poorly on those challenging tasks, with an average of 31.51%. Moreover, to demonstrate the effectiveness and value of visual CoT, we construct a scaffolding experiment that provides the first one or two multimodal CoT steps in context. Accuracy rises to 47.99% after one step (**+16.48** pts) and 56.70% after two steps (**+25.19** pts) overall, with gains of up to **+43.77** pts in specific domains. These findings highlight the challenging nature of our dataset, the quality of our reasoning traces, and the value of visual CoT.
3. After fine-tuning ANOLE-7B (Chern et al., 2024) on our training set, we improved the accuracy on our in-distribution test set from 4.2% to 16.9%. When evaluating the resulting model on benchmarks requiring visual reasoning, our ANOLE-ZEBRA-COT-7B model achieves an average improvement of **4.9%** across seven challenging datasets, with a maximum gain of **13.1%** on a visual logic benchmark, as shown in Table 2.
4. We fine-tune BAGEL-7B (Deng et al., 2025), a high-quality multimodal model that cannot natively generate interleaved text and images on our dataset. After fine-tuning, the model is able to inherently generate high-quality visual CoT during its own reasoning process, making it well-suited for future RL training, as shown qualitatively in the examples in Figure 4 and Appendix B.

2 RELATED WORK

Visual chain of thought. The community has predominantly been tackling visual CoT by using visual programming to generate images (Surís et al., 2023; Zhang et al., 2023; Mitra et al., 2024; Yang* et al., 2023; Wu and Xie, 2024; Hu et al., 2024; Menon et al., 2024; OpenAI, 2025b; Zheng et al., 2025). In particular, VISUAL SKETCHPAD (Hu et al., 2024) presents the most versatile open-source visual reasoning agents among existing works, handling a wide range of tasks. Another line of work explores model-generated images: for example, Rose et al. (2023) uses a diffusion model to bridge gaps in storytelling, and Chern et al. (2025) generates intermediate images to improve image generation tasks; Zhao et al. (2025) generates intermediate images as subgoal predictions and derives actions based on them for robotic planning; Li et al. (2025) and Xu et al. (2025b) explore spatial reasoning tasks like mazes by visualizing each temporal step. However, these model-generated

image approaches are mostly specialists, and developments are still primitive compared to visual programming methods that leverage external tools.

Visual reasoning datasets. Many multimodal visual reasoning datasets have been proposed, such as GQA (Hudson and Manning, 2019), SCIENCEQA (Lu et al., 2022), VIDEOCOT (Wang et al., 2024c), EGOCOT (Mu et al., 2023), LLAVA-COT (Xu et al., 2024), MAMMOTH-VL (Guo et al., 2024), MM-VERIFY (Sun et al., 2025), R1-ONEVISION (Yang et al., 2025), CLEVR (Johnson et al., 2017), VCR (Zellers et al., 2019), although most focus on multi-modality only in the input question, leaving the reasoning traces purely textual. Among them, VISUAL-COT (Shao et al., 2024a) stands out as the only open-source dataset featuring interleaved text and image reasoning. MM-PHYQA (Anand et al., 2024) on the other hand, introduces a paradigm for incorporating images into the reasoning process for physics problems, though the dataset is not publicly available. Several vision-centric benchmarks (Fu et al., 2024b; Hao et al., 2025a) present diverse and challenging tasks, but they lack annotated reasoning traces.

Interleaved text and image datasets. Large-scale corpora with interleaved text and images have become essential for pretraining VLMs with reasoning capabilities (Alayrac et al., 2022; Chen and Wang, 2022; Sun et al., 2024; Wang et al., 2024b; Hurst et al., 2024; Li et al., 2024a; Bai et al., 2025; Team et al., 2025). However, in most existing interleaved text and image datasets MULTIMODAL C4 (Zhu et al., 2023), OBELICS (Laurençon et al., 2023), OMNICORPUS (Li et al., 2024b), images are primarily used for recognition, captioning, or as supplementary context in text-based reasoning, rather than serving as explicit visual aids that contribute meaningfully to the reasoning process. While MINT-1T (Awadalla et al., 2024) includes some scientific content from arXiv where images may aid reasoning, both the text traces and visual content are often noisy and not well-suited for post-training or fine-grained reasoning tasks. Instead, our ZEBRA-COT introduces a broader and higher-quality set of visual CoT examples, enabling effective training for visual reasoning.

3 DATA CURATION DETAILS AND COMPOSITIONS

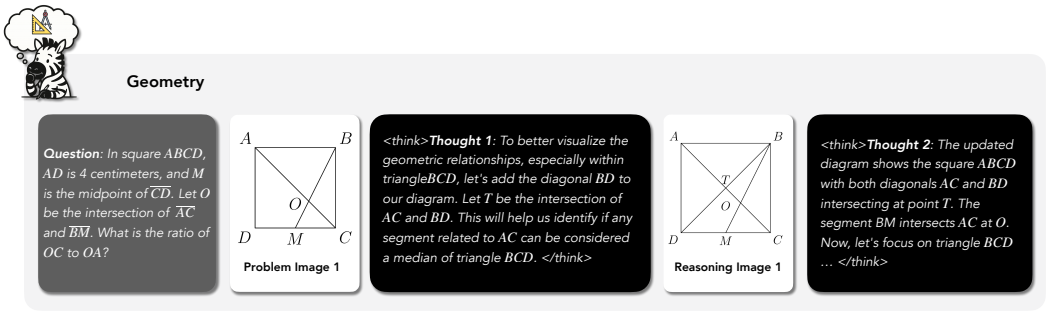
3.1 CURATING A DIVERSE AND HIGH QUALITY INTERLEAVED VISION AND LANGUAGE REASONING DATASET

A key challenge in training multimodal generation models to output visual CoT natively is the lack of datasets with strong logical coherence between text and visual modalities, and diverse categories of such visual CoT. Existing interleaved datasets often fail to provide clear, meaningful connections that demonstrate when and why visual reasoning is necessary for problem-solving, while current visual CoT datasets are confined to a few domains, limiting the model's ability to learn generalizable visual CoT capabilities when faced with out-of-distribution problems.

To address these gaps, we developed a comprehensive data curation pipeline that bridges logical connections across modalities, as shown in Figure 5. For logical coherence across modalities, we leverage frontier vision-language models (Gemini-2.5 Pro) to enrich reasoning traces and ensure a clear logical flow between textual reasoning and visual aids. For diversity, we combine real-world problems from multiple domains (mathematics, physics, chemistry, coding, chess, visual question answering, robotics) with synthetic examples generated through computer programming, simulation, and graphic rendering. This pipeline enabled us to curate over 182 K high-quality interleaved text and visual reasoning traces spanning four major categories: scientific reasoning, 2D visual reasoning, 3D visual reasoning, and visual logic and strategic games. Unlike existing limited datasets that focus primarily on visual search or spatial reasoning, our curated dataset provides the breadth and diversity necessary for training models that can generalize across domains. For details regarding our data curation pipeline, please refer to Appendix A.2. In the following sections, we provide a brief introduction to the tasks of each broad category. And for the details regarding the subcategory and domains, please refer to Appendices A.3 to A.6. For prompt templates, please refer to Appendix F.

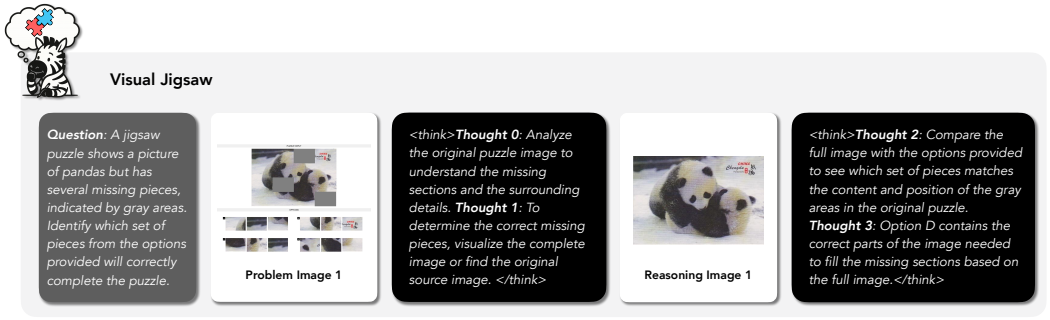
3.2 SCIENTIFIC QUESTIONS

Visual reasoning is particularly valuable in STEM domains, as it enables the visualization of abstract concepts such as auxiliary lines, free-body diagrams, and sketches, which clarify ideas that are hard



to describe in language and support step-by-step problem solving in ways that mirror human cognition. In ZEBRA-COT, this category spans subdomains including geometry, physics, chemistry, algorithmic problem solving, and graph problems. For geometry, physics, and chemistry, we leverage openly licensed datasets and textbooks, using Gemini-2.5 (Comanici et al., 2025) to denoise and parse them into clean, logically structured visual CoT. For graph problems, we employ computer programs to generate images and text templates, which are then diversified using Gemini-2.5. For algorithmic problems, we use a GPT-4.1 agent built upon Hu et al. (2024) to produce detailed traces for solving competitive programming tasks. For details regarding all tasks in this domain, see Appendix A.3.

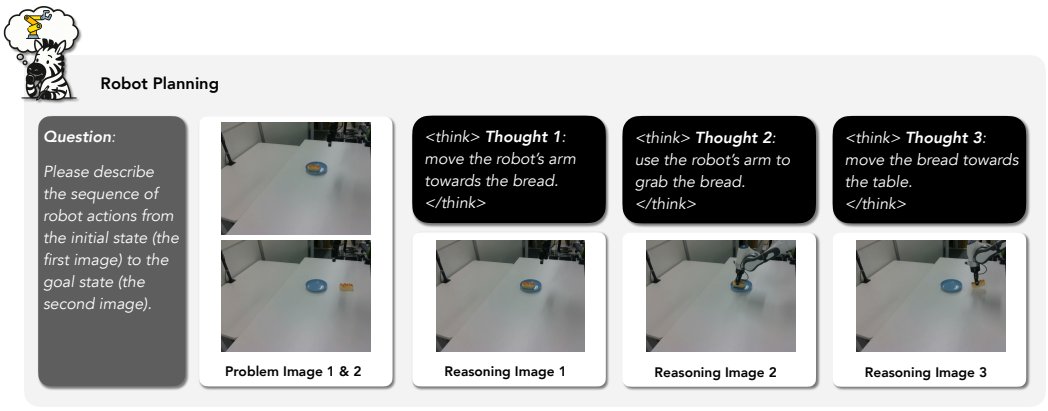
3.3 2D VISUAL REASONING



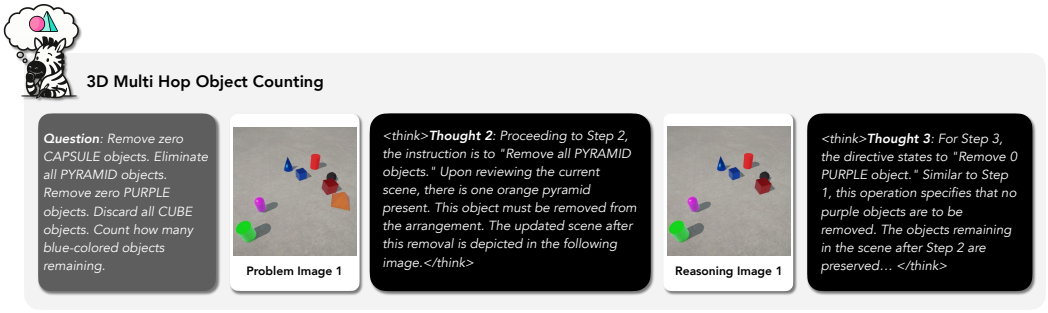
In 2D visual reasoning, visual aids support the manipulation and interpretation of 2D visual information, enabling tasks that involve spatial arrangement, pattern recognition, and fine-grained inspection. For this category, we include tasks such as visual search and visual jigsaw. For visual search, we adapt datasets from Shao et al. (2024a) and incorporate two types of visual aids: drawing bounding boxes and zooming into focal regions. We apply those visual CoT broadly across data categories, such as charts, documents, relations, and general VQA. For visual jigsaw tasks, we crop images from ImageNet (Deng et al., 2009) to create puzzles with a random number of missing pieces in diverse shapes. The visual CoT is either iteratively filling in the pieces or reconstructing the original image directly. Further details are provided in Appendix A.4.

3.4 3D VISUAL REASONING

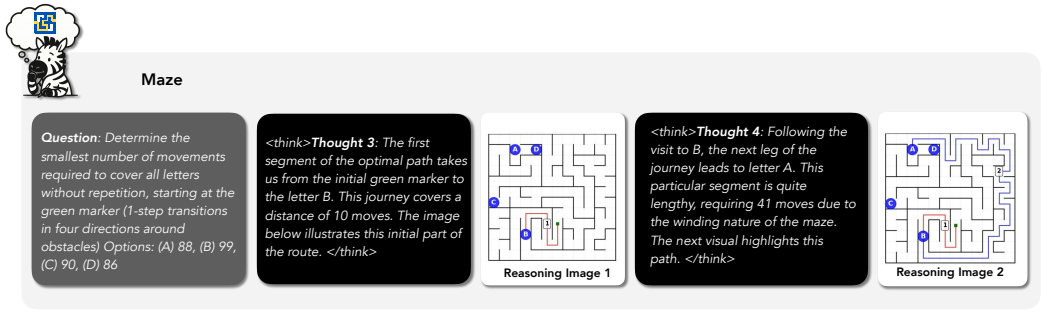
For 3D visual reasoning tasks, we focus on two domains: (1) embodied reasoning and robotic planning in the physical world, and (2) understanding 3D transformations from different viewpoints. For the first domain, prior work has shown that generating visual predictions of the physical world and extracting inverse dynamics can improve performance in long-horizon decision-making in robotics (Zhao et al., 2025; Yang et al., 2024). To capture this, we reformulate the ALFRED benchmark (Shridhar et al., 2020) into an image goal-conditioned planning task in which models generate detailed step-by-step plans to transition from an initial state to a goal state. We also adapt RoboMIND (Wu et al., 2024) for real-world robot planning, where models receive initial and goal images, along with descriptions of robot embodiment, and must produce precise high-level action plans. For reasoning about 3D transformations, we design multi-hop object counting tasks inspired



by CLEVR (Johnson et al., 2017), where scenes undergo sequential modifications, such as adding or removing objects, requiring models to visually reason through each transformation step. For details, see Appendix A.5



3.5 Visual Logic and Strategic Games



For visual logic puzzles (IQ matrices, Tetris, ciphers, ARC-AGI (Chollet et al., 2024)), previous VLMs tended to solve problems primarily using text reasoning. They first verbalize visual inputs into text, which causes information loss and makes visually salient patterns, such as spatial relationships, difficult to capture. In contrast, humans solve these directly and efficiently via visual imagination and manipulation, even for babies who have not yet acquired language capabilities (Zhu et al., 2020). To bridge the gap, we construct visual CoT traces that include explicit intermediate visual transformations to encourage models to solve these problems visually. Similarly, for strategic games (chess, checkers, Connect Four), decision making typically involves searching and generating counterfactual rollouts. While LLMs can simulate this by symbolizing board states into text, much of the spatial structure is lost, and rollouts in text space are difficult for problems with large visual information. Thus, we render those search and simulation steps into images so that models trained on this data can perform long-horizon planning in the visual space inherently. Finally, we generate a diverse suite of maze tasks and visual CoT traces that require a combination of capabil-

ities, including high-level symbolic search and low-level perception. For details of those tasks, see Appendix A.6.

4 Analysis of Zebra-CoT and the Value of visual CoT

Proprietary frontier models (GPT-5 (OpenAI, 2025c), Gemini-2.5 Pro (Comanici et al., 2025), Claude-4 Sonnet (Anthropic, 2025)) have achieved state-of-the-art performance on multimodal reasoning benchmarks. Despite their advanced multimodal capabilities, we show that they struggle significantly with the tasks in Zebra-CoT. To explore these limitations and demonstrate the challenging nature of our dataset alongside the effectiveness of visual reasoning traces, we design a scaffolding experiment. Specifically, our dataset consists of structured reasoning chains: `<question>` → `<text-reasoning-1>` → `<visual-reasoning-1>` → `<text-reasoning-2>` → `<visual-reasoning-2>` → ... → `<answer>`.

In the zero-shot setting, we provide models only with the `<question>` (containing both image and text). For scaffolding experiments, we incrementally provide the first k multimodal reasoning steps as context:

- **1MT** ($k = 1$): `<question>` + `<text-reasoning-1>` + `<visual-reasoning-1>`
- **2MT** ($k = 2$): `<question>` + `<text-reasoning-1>` + `<visual-reasoning-1>` + `<text-reasoning-2>` + `<visual-reasoning-2>`

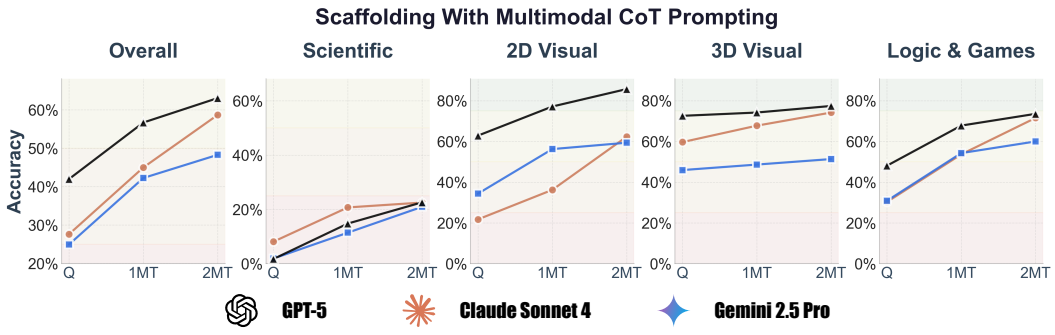


Figure 3: Scaffolding experiment with frontier models. **Q** represents zero-shot question-only evaluation, **1MT** denotes a question with the first multimodal reasoning step provided, and **2MT** indicates a question with the first two multimodal reasoning steps. We show that **even frontier models with the best multimodal reasoning capabilities perform poorly overall on tasks in Zebra-CoT**. However, as we provide the first one or two multimodal steps to those models, the accuracy improves significantly.

Importantly, most tasks in Zebra-CoT require various multimodal reasoning steps (which can involve as many as 20 images) to reach the final answer. By providing only the first two steps as scaffolding, we ensure that models must still perform substantial reasoning to solve the task. We can safely assume that the provided steps serve as guidance rather than revealing the solution. Since our dataset comprises diverse tasks, some of which extend beyond traditional QA formats (e.g., robotic planning and embodied CoT) that are not suitable for evaluation, we select the most challenging and

representative examples for evaluation: graph questions for scientific reasoning, visual jigsaw for 2D spatial reasoning, multihop object counting for 3D reasoning, and maze/chess/tetris for visual logic and strategic games.

We plot the results for three evaluation settings across each task domain in Figure 3. We observe that frontier models achieve poor zero-shot performance: GPT-5 reaches 41.98% accuracy, while Claude-4 Sonnet and Gemini-2.5 Pro achieve only 27.61% and 24.93% respectively. However, with multimodal CoT scaffolding, we observe substantial improvements: average accuracy across the three models increases to 47.99% (**+16.48%**) with one reasoning step and 56.70% (**+25.19%**) with two steps.

Performance gains vary across task types, but we generally see an improvement trend. Maze tasks show the most dramatic improvements, which jump from 52.59% to 76.60% (+24.01%) and to 96.36% (+43.77%) on average, while challenging tasks such as graph reasoning improve from 3.92% to 22.03% (+18.11%) with two multimodal reasoning steps on average. Even tasks with higher baseline performance, such as multihop object counting (with an initial accuracy of 59.40%), benefit from visual CoT, eventually reaching 67.65% accuracy on average. Detailed statistics are shown in Table 8.

To isolate the contribution of visual reasoning aids from text CoT in our traces, we conduct an ablation task where we remove all visual aids from the reasoning traces and retain only the textual steps. We observe that text-only CoT yields substantially smaller performance gains compared to full visual CoT, and in some cases even degrades performance. This is expected: in our dataset, the visual and textual components are highly complementary. Many reasoning steps reference visual elements that, once removed, leave the text chain logically incomplete or incoherent. Model even requests for the missing visual aids that are referred in the text cot. These results indicate that the majority of the performance improvements stem from the visual reasoning steps, or the combined visual + text reasoning, rather than from textual CoT alone. The statistics for text only results are shown here:

5 Training Models on Zebra-CoT

Model	MathVision*	MathVista*	VisuLogic	EMMA	MMVP	Blink	Vstar
Anole with CoT prompting	13.80	22.80	8.50	12.80	10.00	26.46	23.60
Anole–Zebra-CoT (Ours)	**16.45**	**25.30**	**21.80**	**15.02**	**15.33**	**31.25**	**27.20**

Table 2: Overall performance (%) across eight datasets for the base Anole model with chain-of-thought prompting vs. the same Anole model further trained on Zebra-CoT. *We evaluate on the mini versions of MathVision and MathVista because interleaved generation is time consuming. A full breakdown of each evaluation set is presented in Appendix C.

Anole-Zebra-CoT. We fine-tune Anole (Chern et al., 2024) on our dataset, which builds on Chameleon (Team, 2024), using the codebase from Chern et al. (2025). We finetune the model fully end-to-end on a node with 8 × H200 GPUs for 12 hours, with a learning rate of 1×10^{-5}, cosine decay, a batch size of 8, and a max token length of 12288. We train the model for 10k steps. To evaluate our trained model, we set the maximum generation length to 16384. After fine-tuning Anole on our Zebra-CoT corpus, the accuracy increased from 4.2% to 16.9%, delivering a 4 times relative performance improvement and a 12% gain in accuracy.

Furthermore, we evaluate seven challenging benchmarks that require visual reasoning, including `MathVision` (Wang et al., 2024a), `MathVista` (Lu et al., 2024), `VisuLogic` (Xu et al., 2025a), `EMMA` (Hao et al., 2025b), `MMVP` (Tong et al., 2024), `BLINK` (Fu et al., 2024b), and `Vstar` (Wang et al., 2023). All the evaluations are done using `VLMEvalKit` (Duan et al., 2024). To ensure a fair comparison, we use chain-of-thought prompting (Wei et al., 2022) when evaluating the base Anole model. As shown in Table 2, training with Zebra-CoT significantly improves the Anole model across all benchmarks. Most notably, it could improve the Anole model's visual logical reasoning capabilities by 13.3 points.

Bagel-Zebra-CoT. To further test whether Zebra-CoT can enhance a stronger backbone, we fine-tune the Bagel-7B model (Deng et al., 2025) end-to-end on a node with 8× H200 GPUs for 1,000

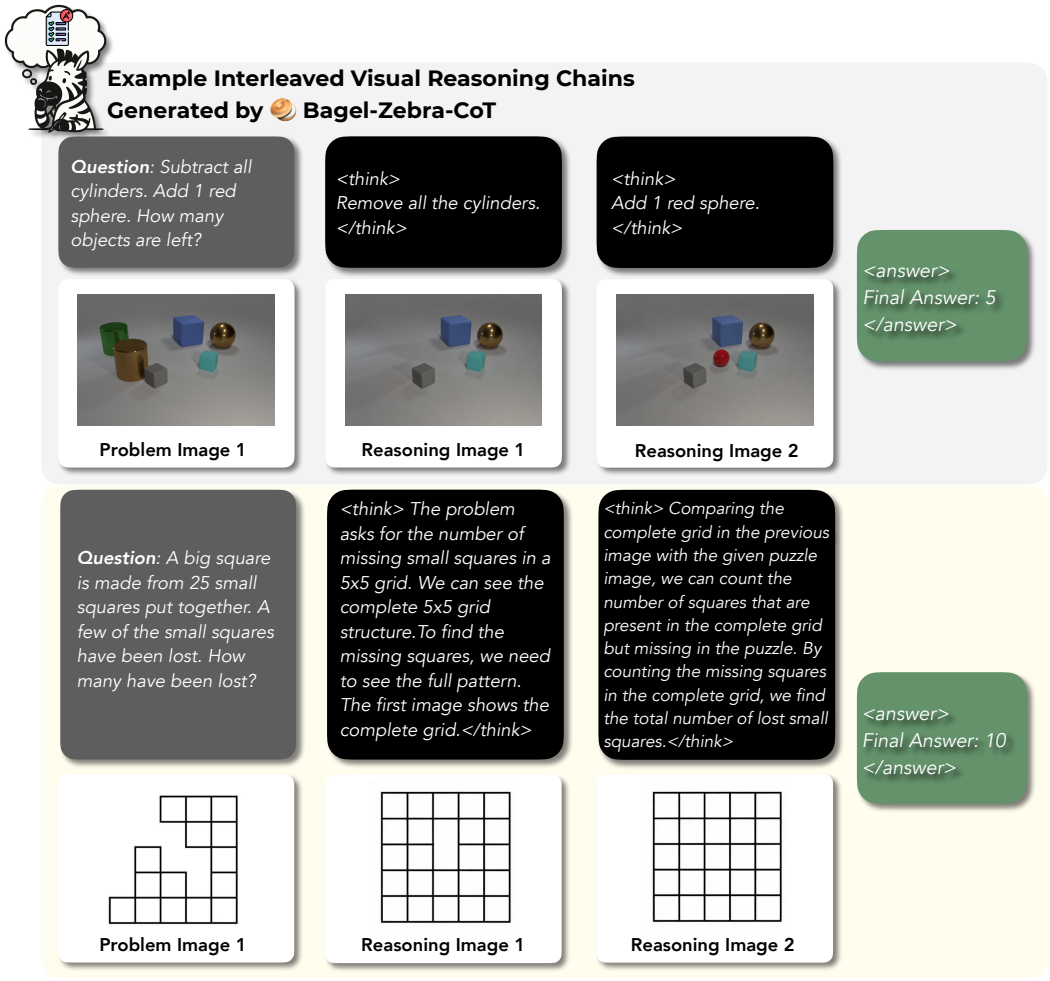


Figure 4: Example interleaved reasoning chains generated by Bagel-Zebra-CoT, a Bagel-7B model finetuned on ZEBRA-COT. These traces demonstrate ZEBRA-COT's for instilling intrinsic visual reasoning capability in complex multimodal models.

steps using packed sequences with 60,000 tokens, a learning rate of 2×10^{-5}, and cosine decay. We cap all images at a resolution of 512 on the minimum side, resulting in approximately $1,024+$ visual tokens per image. Because the original Bagel implementation cannot natively generate interleaved text–image outputs, we revise the training loop to include a loss term at the `<|vision_start|>` token, enabling seamless visual token generation. We additionally wrap text reasoning tokens between `<think>` and `</think>`, and the final answer within `<answer>` and `</answer>`. At inference time, when encountering `<im_end>`, we sample one additional token to check whether the next token is `<|vision_start|>`; if so, the model itself seamlessly switches to image generation mode to generate visual aids. The entire interleaved generation process only stops if the model generates the `<answer>` token.

We observe that our trained model can inherently generate visual CoT when solving problems, even on tasks outside its training distribution. This suggests its potential as a strong initialization for future reinforcement learning fine-tuning. In Figure 4, we include representative reasoning traces produced by the model. We further include more reasoning traces in Appendix B, as well as a model performance analysis in Appendix D

6 CONCLUSION & FUTURE DIRECTIONS

In this paper, we introduced ZEBRA-COT, a large-scale dataset of 182K interleaved text-image reasoning traces spanning 4 major categories across 18 domains with over 50 distinct tasks. Fine-tuning experiments demonstrate substantial improvements: Anole-7B achieves an average 4.9 % gain across seven challenging benchmarks, with up to 13.1% on visual logic tasks, while Bagel-7B learns to inherently generate visual aids during problem solving, a capability absent in the base model.

This work opens several exciting avenues for future research. Most immediately, models trained on ZEBRA-COT, particularly our Bagel variant that natively generates visual thoughts, provide strong initializations for reinforcement learning. Just as text-based reasoning models have benefited from RL fine-tuning to improve logical consistency and correctness, we envision similar gains for visual reasoning through RL with verifiable rewards (Shao et al., 2024b; Guo et al., 2025) or fine-grained rewards (Zeng et al., 2024; Fu et al., 2025).

We believe ZEBRA-COT represents a crucial step toward AI systems that think visually as naturally as humans sketch diagrams, generate graphs, and use spatial reasoning to solve complex problems. With our dataset and fine-tuned model, we hope to accelerate progress toward this goal.

7 LLM USAGE DISCLOSURE

We used LLM for two purposes. The first one is for improving grammar and wording when writing the paper. The second usage is synthetic data generation, where details can be found in Section 3 and Appendix A.2

REFERENCES

AgileX Robotics. Cobot magic. https://global.agilex.ai/products/cobot-magic, 2023.

Jean-Baptiste Alayrac, Jeff Donahue, Pauline Luc, Antoine Miech, Iain Barr, Yana Hasson, Karel Lenc, Arthur Mensch, Katie Millican, Malcolm Reynolds, Roman Ring, Eliza Rutherford, Serkan Cabi, Tengda Han, Zhitao Gong, Sina Samangooei, Marianne Monteiro, Jacob Menick, Sebastian Borgeaud, Andrew Brock, Aida Nematzadeh, Sahand Sharifzadeh, Mikolaj Binkowski, Ricardo Barreira, Oriol Vinyals, Andrew Zisserman, and Karen Simonyan. Flamingo: a visual language model for few-shot learning. 2022. URL https://arxiv.org/abs/2204.14198.

Avinash Anand, Janak Kapuriya, Apoorv Singh, Jay Saraf, Naman Lal, Astha Verma, Rushali Gupta, and Rajiv Shah. Mm-phyqa: Multimodal physics question-answering with multi-image cot prompting. In *Pacific-Asia Conference on Knowledge Discovery and Data Mining*, pages 53–64. Springer, 2024.

Anthropic. System card: Claude opus 4 & claude sonnet 4. System card, Anthropic, May 2025. URL https://www-cdn.anthropic.com/6d8a8055020700718b0c49369f60816ba2a7c285.pdf. Original May 2025; changelog entries July 16, 2025 and Sept 2, 2025.

Anas Awadalla, Le Xue, Oscar Lo, Manli Shu, Hannah Lee, Etash Guha, Sheng Shen, Mohamed Awadalla, Silvio Savarese, Caiming Xiong, et al. Mint-1t: Scaling open-source multimodal data by 10x: A multimodal dataset with one trillion tokens. *Advances in Neural Information Processing Systems*, 37:36805–36828, 2024.

Shuai Bai, Keqin Chen, Xuejing Liu, Jialin Wang, Wenbin Ge, Sibo Song, Kai Dang, Peng Wang, Shijie Wang, Jun Tang, et al. Qwen2. 5-vl technical report. *arXiv preprint arXiv:2502.13923*, 2025.

Greg Brockman, Vicki Cheung, Ludwig Pettersson, Jonas Schneider, John Schulman, Jie Tang, and Wojciech Zaremba. Openai gym. *arXiv preprint arXiv:1606.01540*, 2016.

Xi Chen and Xiao Wang. Pali: Scaling language-image learning in 100+ languages. In *Conference on Neural Information Processing Systems (NeurIPS)*, 2022.

Ethan Chern, Jiadi Su, Yan Ma, and Pengfei Liu. Anole: An open, autoregressive, native large multimodal models for interleaved image-text generation. *arXiv preprint arXiv:2407.06135*, 2024.

Ethan Chern, Zhulin Hu, Steffi Chern, Siqi Kou, Jiadi Su, Yan Ma, Zhijie Deng, and Pengfei Liu. Thinking with generated images. *arXiv preprint arXiv:2505.22525*, 2025.

François Chollet. On the measure of intelligence. *arXiv preprint arXiv:1911.01547*, 2019.

Francois Chollet, Mike Knoop, Gregory Kamradt, and Bryan Landers. Arc prize 2024: Technical report. *arXiv preprint arXiv:2412.04604*, 2024.

Gheorghe Comanici, Eric Bieber, Mike Schaekermann, Ice Pasupat, Noveen Sachdeva, Inderjit Dhillon, Marcel Blistein, Ori Ram, Dan Zhang, Evan Rosen, et al. Gemini 2.5: Pushing the frontier with advanced reasoning, multimodality, long context, and next generation agentic capabilities. *arXiv preprint arXiv:2507.06261*, 2025.

Joost CF de Winter, Dimitra Dodou, and Yke Bauke Eisma. Responses to raven matrices: Governed by visual complexity and centrality. *Perception*, 52(9):645–661, 2023.

Chaorui Deng, Deyao Zhu, Kunchang Li, Chenhui Gou, Feng Li, Zeyu Wang, Shu Zhong, Weihao Yu, Xiaonan Nie, Ziang Song, et al. Emerging properties in unified multimodal pretraining. *arXiv preprint arXiv:2505.14683*, 2025.

Jia Deng, Wei Dong, Richard Socher, Li-Jia Li, Kai Li, and Li Fei-Fei. Imagenet: A large-scale hierarchical image database. In *2009 IEEE conference on computer vision and pattern recognition*, pages 248–255. Ieee, 2009.

Haodong Duan, Junming Yang, Yuxuan Qiao, Xinyu Fang, Lin Chen, Yuan Liu, Xiaoyi Dong, Yuhang Zang, Pan Zhang, Jiaqi Wang, et al. Vlmevalkit: An open-source toolkit for evaluating large multi-modality models. In *Proceedings of the 32nd ACM International Conference on Multimedia*, pages 11198–11201, 2024.

Franka Emika GmbH. *Franka Emika Panda Robot Arm*, 2018. https://www.franka.de.

Deqing Fu, Ruohao Guo, Ghazal Khalighinejad, Ollie Liu, Bhuwan Dhingra, Dani Yogatama, Robin Jia, and Willie Neiswanger. IsoBench: Benchmarking multimodal foundation models on isomorphic representations. In *First Conference on Language Modeling (COLM)*, 2024a.

Deqing Fu, Tong Xiao, Rui Wang, Wang Zhu, Pengchuan Zhang, Guan Pang, Robin Jia, and Lawrence Chen. TLDR: Token-level detective reward model for large vision language models. In *The Thirteenth International Conference on Learning Representations*, 2025. URL https://openreview.net/forum?id=Zy2XgaGpDw.

Xingyu Fu, Yushi Hu, Bangzheng Li, Yu Feng, Haoyu Wang, Xudong Lin, Dan Roth, Noah A Smith, Wei-Chiu Ma, and Ranjay Krishna. Blink: Multimodal large language models can see but not perceive. In *European Conference on Computer Vision*, pages 148–166. Springer, 2024b.

Daya Guo, Dejian Yang, Haowei Zhang, Junxiao Song, Ruoyu Zhang, Runxin Xu, Qihao Zhu, Shirong Ma, Peiyi Wang, Xiao Bi, et al. Deepseek-r1: Incentivizing reasoning capability in llms via reinforcement learning. *arXiv preprint arXiv:2501.12948*, 2025.

Jarvis Guo, Tuney Zheng, Yuelin Bai, Bo Li, Yubo Wang, King Zhu, Yizhi Li, Graham Neubig, Wenhu Chen, and Xiang Yue. Mammoth-vl: Eliciting multimodal reasoning with instruction tuning at scale. *arXiv preprint arXiv:2412.05237*, 2024.

Yunzhuo Hao, Jiawei Gu, Huichen Will Wang, Linjie Li, Zhengyuan Yang, Lijuan Wang, and Yu Cheng. Can mllms reason in multimodality? emma: An enhanced multimodal reasoning benchmark. *arXiv preprint arXiv:2501.05444*, 2025a.

Yunzhuo Hao, Jiawei Gu, Huichen Will Wang, Linjie Li, Zhengyuan Yang, Lijuan Wang, and Yu Cheng. Can mllms reason in multimodality? emma: An enhanced multimodal reasoning benchmark. *arXiv preprint arXiv:2501.05444*, 2025b.

Dan Hendrycks, Collin Burns, Saurav Kadavath, Akul Arora, Steven Basart, Eric Tang, Dawn Song, and Jacob Steinhardt. Measuring mathematical problem solving with the MATH dataset. In *Thirty-fifth Conference on Neural Information Processing Systems Datasets and Benchmarks Track (Round 2)*, 2021. URL https://openreview.net/forum?id=7Bywt2mQsCe.

Yushi Hu, Weijia Shi, Xingyu Fu, Dan Roth, Mari Ostendorf, Luke Zettlemoyer, Noah A Smith, and Ranjay Krishna. Visual sketchpad: Sketching as a visual chain of thought for multimodal language models. *arXiv preprint arXiv:2406.09403*, 2024.

Drew A Hudson and Christopher D Manning. Gqa: A new dataset for real-world visual reasoning and compositional question answering. In *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition*, pages 6700–6709, 2019.

Aaron Hurst, Adam Lerer, Adam P Goucher, Adam Perelman, Aditya Ramesh, Aidan Clark, AJ Ostrow, Akila Welihinda, Alan Hayes, Alec Radford, et al. Gpt-4o system card. *arXiv preprint arXiv:2410.21276*, 2024.

Michael Igorevich Ivanitskiy, Rusheb Shah, Alex F. Spies, Tilman Räuker, Dan Valentine, Can Rager, Lucia Quirke, Chris Mathwin, Guillaume Corlouer, Cecilia Diniz Behn, and Samy Wu Fung. A configurable library for generating and manipulating maze datasets, 2023. URL https://arxiv.org/abs/2309.10498.

Justin Johnson, Bharath Hariharan, Laurens Van Der Maaten, Li Fei-Fei, C Lawrence Zitnick, and Ross Girshick. Clevr: A diagnostic dataset for compositional language and elementary visual reasoning. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 2901–2910, 2017.

Alex Lau-Zhu, Emily A Holmes, Sally Butterfield, and Joni Holmes. Selective association between tetris game play and visuospatial working memory: A preliminary investigation. *Applied cognitive psychology*, 31(4):438–445, 2017.

Hugo Laurençon, Lucile Saulnier, Léo Tronchon, Stas Bekman, Amanpreet Singh, Anton Lozhkov, Thomas Wang, Siddharth Karamcheti, Alexander M. Rush, Douwe Kiela, Matthieu Cord, and Victor Sanh. Obelics: An open web-scale filtered dataset of interleaved image-text documents, 2023.

Chengzu Li, Wenshan Wu, Huanyu Zhang, Yan Xia, Shaoguang Mao, Li Dong, Ivan Vulić, and Furu Wei. Imagine while reasoning in space: Multimodal visualization-of-thought. *arXiv preprint arXiv:2501.07542*, 2025.

Feng Li, Renrui Zhang, Hao Zhang, Yuanhan Zhang, Bo Li, Wei Li, Zejun Ma, and Chunyuan Li. Llava-next-interleave: Tackling multi-image, video, and 3d in large multimodal models. *arXiv preprint arXiv:2407.07895*, 2024a.

Qingyun Li, Zhe Chen, Weiyun Wang, Wenhai Wang, Shenglong Ye, Zhenjiang Jin, Guanzhou Chen, Yinan He, Zhangwei Gao, Erfei Cui, et al. Omnicorpus: A unified multimodal corpus of 10 billion-level images interleaved with text. *arXiv preprint arXiv:2406.08418*, 2024b.

Pan Lu, Swaroop Mishra, Tanglin Xia, Liang Qiu, Kai-Wei Chang, Song-Chun Zhu, Oyvind Tafjord, Peter Clark, and Ashwin Kalyan. Learn to explain: Multimodal reasoning via thought chains for science question answering. *Advances in Neural Information Processing Systems*, 35:2507–2521, 2022.

Pan Lu, Hritik Bansal, Tony Xia, Jiacheng Liu, Chunyuan Li, Hannaneh Hajishirzi, Hao Cheng, Kai-Wei Chang, Michel Galley, and Jianfeng Gao. Mathvista: Evaluating mathematical reasoning of foundation models in visual contexts. In *International Conference on Learning Representations (ICLR)*, 2024.

Sachit Menon, Richard Zemel, and Carl Vondrick. Whiteboard-of-thought: Thinking step-by-step across modalities. *arXiv preprint arXiv:2406.14562*, 2024.

MIT OpenCourseWare. [Course Title]. https://ocw.mit.edu/, 2022. MIT OpenCourseWare: Massachusetts Institute of Technology. License: Creative Commons BY-NC-SA.

Chancharik Mitra, Brandon Huang, Trevor Darrell, and Roei Herzig. Compositional chain-of-thought prompting for large multimodal models. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 14420–14431, 2024.

William Moebs, Samuel J. Ling, and Jeff Sanny. *University Physics Volume 1*. OpenStax, Houston, Texas, 2016. URL https://openstax.org/books/university-physics-volume-1/pages/1-introduction. Licensed under CC BY 4.0.

Yao Mu, Qinglong Zhang, Mengkang Hu, Wenhai Wang, Mingyu Ding, Jun Jin, Bin Wang, Jifeng Dai, Yu Qiao, and Ping Luo. Embodiedgpt: Vision-language pre-training via embodied chain of thought. *Advances in Neural Information Processing Systems*, 36:25081–25094, 2023.

OpenAI. Openai o3 and o4-mini system card. Technical report, OpenAI, April 2025a. URL https://cdn.openai.com/pdf/2221c875-02dc-4789-800b-e7758f3722c1/o3-and-o4-mini-system-card.pdf.

OpenAI. Thinking with images. https://openai.com/index/thinking-with-images/, April 2025b. Accessed: 2025-07-21.

OpenAI. Gpt-5 system card, August 2025c. URL https://openai.com/index/gpt-5-system-card/. System card for GPT-5.

Bharath Ramsundar, Peter Eastman, Patrick Walters, Vijay Pande, Karl Leswing, and Zhenqin Wu. *Deep Learning for the Life Sciences*. O'Reilly Media, 2019. https://www.amazon.com/Deep-Learning-Life-Sciences-Microscopy/dp/1492039837.

Daniel Rose, Vaishnavi Himakunthala, Andy Ouyang, Ryan He, Alex Mei, Yujie Lu, Michael Saxon, Chinmay Sonar, Diba Mirza, and William Yang Wang. Visual chain of thought: bridging logical gaps with multimodal infillings. *arXiv preprint arXiv:2305.02317*, 2023.

Hao Shao, Shengju Qian, Han Xiao, Guanglu Song, Zhuofan Zong, Letian Wang, Yu Liu, and Hongsheng Li. Visual cot: Advancing multi-modal language models with a comprehensive dataset and benchmark for chain-of-thought reasoning. *Advances in Neural Information Processing Systems*, 37:8612–8642, 2024a.

Zhihong Shao, Peiyi Wang, Qihao Zhu, Runxin Xu, Junxiao Song, Xiao Bi, Haowei Zhang, Mingchuan Zhang, Y. K. Li, Y. Wu, and Daya Guo. Deepseekmath: Pushing the limits of mathematical reasoning in open language models, 2024b. URL https://arxiv.org/abs/2402.03300.

Mohit Shridhar, Jesse Thomason, Daniel Gordon, Yonatan Bisk, Winson Han, Roozbeh Mottaghi, Luke Zettlemoyer, and Dieter Fox. ALFRED: A Benchmark for Interpreting Grounded Instructions for Everyday Tasks. In *The IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, 2020. URL https://arxiv.org/abs/1912.01734.

Linzhuang Sun, Hao Liang, Jingxuan Wei, Bihui Yu, Tianpeng Li, Fan Yang, Zenan Zhou, and Wentao Zhang. Mm-verify: Enhancing multimodal reasoning with chain-of-thought verification. *arXiv preprint arXiv:2502.13383*, 2025.

Quan Sun, Yufeng Cui, Xiaosong Zhang, Fan Zhang, Qiying Yu, Yueze Wang, Yongming Rao, Jingjing Liu, Tiejun Huang, and Xinlong Wang. Generative multimodal models are in-context learners. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 14398–14409, 2024.

Dídac Surís, Sachit Menon, and Carl Vondrick. Vipergpt: Visual inference via python execution for reasoning. In *Proceedings of the IEEE/CVF International Conference on Computer Vision*, pages 11888–11898, 2023.

Chameleon Team. Chameleon: Mixed-modal early-fusion foundation models. *arXiv preprint arXiv:2405.09818*, 2024.

Gemini Team, Rohan Anil, Sebastian Borgeaud, Jean-Baptiste Alayrac, Jiahui Yu, Radu Soricut, Johan Schalkwyk, Andrew M Dai, Anja Hauth, Katie Millican, et al. Gemini: a family of highly capable multimodal models. *arXiv preprint arXiv:2312.11805*, 2023.

Gemma Team, Aishwarya Kamath, Johan Ferret, Shreya Pathak, Nino Vieillard, Ramona Merhej, Sarah Perrin, Tatiana Matejovicova, Alexandre Ramé, Morgane Rivière, et al. Gemma 3 technical report. *arXiv preprint arXiv:2503.19786*, 2025.

Shengbang Tong, Zhuang Liu, Yuexiang Zhai, Yi Ma, Yann LeCun, and Saining Xie. Eyes wide shut? exploring the visual shortcomings of multimodal llms, 2024.

Universal Robots A/S. *UR5e Collaborative Robot Arm*, 2018. https://www.universal-robots.com/products/ur5e/.

Ke Wang, Junting Pan, Weikang Shi, Zimu Lu, Houxing Ren, Aojun Zhou, Mingjie Zhan, and Hongsheng Li. Measuring multimodal mathematical reasoning with math-vision dataset. In *The Thirty-eight Conference on Neural Information Processing Systems Datasets and Benchmarks Track*, 2024a. URL https://openreview.net/forum?id=QWTCcxMpPA.

Xinlong Wang, Xiaosong Zhang, Zhengxiong Luo, Quan Sun, Yufeng Cui, Jinsheng Wang, Fan Zhang, Yueze Wang, Zhen Li, Qiying Yu, et al. Emu3: Next-token prediction is all you need. *arXiv preprint arXiv:2409.18869*, 2024b.

Yan Wang, Yawen Zeng, Jingsheng Zheng, Xiaofen Xing, Jin Xu, and Xiangmin Xu. Videocot: A video chain-of-thought dataset with active annotation tool. *arXiv preprint arXiv:2407.05355*, 2024c.

Yuxuan Wang, Zilong Zheng, Xueliang Zhao, Jinpeng Li, Yueqian Wang, and Dongyan Zhao. VSTAR: A video-grounded dialogue dataset for situated semantic understanding with scene and topic transitions. In *Proceedings of the 61st Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 5036–5048, Toronto, Canada, July 2023. Association for Computational Linguistics. URL https://aclanthology.org/2023.acl-long.276.

Jason Wei, Xuezhi Wang, Dale Schuurmans, Maarten Bosma, Fei Xia, Ed Chi, Quoc V Le, Denny Zhou, et al. Chain-of-thought prompting elicits reasoning in large language models. *Advances in neural information processing systems*, 35:24824–24837, 2022.

Kun Wu, Chengkai Hou, Jiaming Liu, Zhengping Che, Xiaozhu Ju, Zhuqin Yang, Meng Li, Yinuo Zhao, Zhiyuan Xu, Guang Yang, Zhen Zhao, Guangyu Li, Zhao Jin, Lecheng Wang, Jilei Mao, Xinhua Wang, Shichao Fan, Ning Liu, Pei Ren, Qiang Zhang, Yaoxu Lyu, Mengzhen Liu, Jingyang He, Yulin Luo, Zeyu Gao, Chenxuan Li, Chenyang Gu, Yankai Fu, Di Wu, Xingyu Wang, Sixiang Chen, Zhenyu Wang, Pengju An, Siyuan Qian, Shanghang Zhang, and Jian Tang. Robomind: Benchmark on multi-embodiment intelligence normative data for robot manipulation. *arXiv preprint arXiv:2412.13877*, 2024.

Penghao Wu and Saining Xie. V*: Guided visual search as a core mechanism in multimodal llms. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 13084–13094, 2024.

Guowei Xu, Peng Jin, Li Hao, Yibing Song, Lichao Sun, and Li Yuan. Llava-o1: Let vision language models reason step-by-step. *arXiv preprint arXiv:2411.10440*, 2024.

Weiye Xu, Jiahao Wang, Weiyun Wang, Zhe Chen, Wengang Zhou, Aijun Yang, Lewei Lu, Houqiang Li, Xiaohua Wang, Xizhou Zhu, Wenhai Wang, Jifeng Dai, and Jinguo Zhu. Visulogic: A benchmark for evaluating visual reasoning in multi-modal large language models, 2025a. URL https://arxiv.org/abs/2504.15279.

Yi Xu, Chengzu Li, Han Zhou, Xingchen Wan, Caiqi Zhang, Anna Korhonen, and Ivan Vulić. Visual planning: Let's think only with images. *arXiv preprint arXiv:2505.11409*, 2025b.

Sherry Yang, Jacob Walker, Jack Parker-Holder, Yilun Du, Jake Bruce, Andre Barreto, Pieter Abbeel, and Dale Schuurmans. Video as the new language for real-world decision making. *arXiv preprint arXiv:2402.17139*, 2024.

Yi Yang, Xiaoxuan He, Hongkun Pan, Xiyan Jiang, Yan Deng, Xingtao Yang, Haoyu Lu, Dacheng Yin, Fengyun Rao, Minfeng Zhu, et al. R1-onevision: Advancing generalized multimodal reasoning through cross-modal formalization. *arXiv preprint arXiv:2503.10615*, 2025.

Zhengyuan Yang*, Linjie Li*, Jianfeng Wang*, Kevin Lin*, Ehsan Azarnasab*, Faisal Ahmed*, Zicheng Liu, Ce Liu, Michael Zeng, and Lijuan Wang. Mm-react: Prompting chatgpt for multimodal reasoning and action. 2023.

Rowan Zellers, Yonatan Bisk, Ali Farhadi, and Yejin Choi. From recognition to cognition: Visual commonsense reasoning. In *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition*, pages 6720–6731, 2019.

Yongcheng Zeng, Guoqing Liu, Weiyu Ma, Ning Yang, Haifeng Zhang, and Jun Wang. Token-level direct preference optimization. In Ruslan Salakhutdinov, Zico Kolter, Katherine Heller, Adrian Weller, Nuria Oliver, Jonathan Scarlett, and Felix Berkenkamp, editors, *Proceedings of the 41st International Conference on Machine Learning*, volume 235 of *Proceedings of Machine Learning Research*, pages 58348–58365. PMLR, 21–27 Jul 2024. URL https://proceedings.mlr.press/v235/zeng24c.html.

Chi Zhang, Feng Gao, Baoxiong Jia, Yixin Zhu, and Song-Chun Zhu. Raven: A dataset for relational and analogical visual reasoning. In *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition*, pages 5317–5327, 2019.

Zhuosheng Zhang, Aston Zhang, Mu Li, Hai Zhao, George Karypis, and Alex Smola. Multimodal chain-of-thought reasoning in language models. *arXiv preprint arXiv:2302.00923*, 2023.

Qingqing Zhao, Yao Lu, Moo Jin Kim, Zipeng Fu, Zhuoyang Zhang, Yecheng Wu, Zhaoshuo Li, Qianli Ma, Song Han, Chelsea Finn, et al. Cot-vla: Visual chain-of-thought reasoning for vision-language-action models. *arXiv preprint arXiv:2503.22020*, 2025.

Ziwei Zheng, Michael Yang, Jack Hong, Chenxiao Zhao, Guohai Xu, Le Yang, Chao Shen, and Xing Yu. Deepeyes: Incentivizing" thinking with images" via reinforcement learning. *arXiv preprint arXiv:2505.14362*, 2025.

Wang Zhu, Hexiang Hu, Jiacheng Chen, Zhiwei Deng, Vihan Jain, Eugene Ie, and Fei Sha. Baby-Walk: Going farther in vision-and-language navigation by taking baby steps. In *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics*, pages 2539–2556. Association for Computational Linguistics, 2020.

Wanrong Zhu, Jack Hessel, Anas Awadalla, Samir Yitzhak Gadre, Jesse Dodge, Alex Fang, Youngjae Yu, Ludwig Schmidt, William Yang Wang, and Yejin Choi. Multimodal c4: An open, billion-scale corpus of images interleaved with text. *Advances in Neural Information Processing Systems*, 36:8958–8974, 2023.

A Dataset Details

A.1 Data Statistics.

Here we show detailed statistics about Zebra-CoT's categories.

Table 3: Statistics of Zebra-CoT.

General Category	Sub Category	Count	Percentage (%)
2D Visual Reasoning	Visual Jigsaw	21,899	12.0
	Visual Search	30,000	16.4
	Subtotal	**51,899**	**28.5**
3D Visual Reasoning	Embodied Cot	22,666	12.4
	Multi-Hop Objects Counting	10,000	5.5
	Robot Planning	6,944	3.8
	Subtotal	**39,610**	**21.7**
Scientific Reasoning	Chemistry	4,666	2.6
	Competitive Programming	1,207	0.7
	Geometry	1,058	0.6
	Graph Algorithms	10,000	5.5
	Physics	7,090	3.9
	Subtotal	**24,021**	**13.2**
Visual Logic Strategic Games	Arc-Agi	2,000	1.1
	Checkers	2,753	1.5
	Chess	20,483	11.2
	Ciphers	6,589	3.6
	Connect Four	2,029	1.1
	Maze	20,000	11.0
	RPM	3,000	1.6
	Tetris	10,000	5.5
	Subtotal	**66,854**	**36.7**
Total		**182,384**	**100.0**

A.2 Curating Diverse and High Quality visual CoT

Bridging logical connections across modalities. A key challenge in training multimodal generation models to output visual CoT natively is the lack of datasets with strong logical coherence between text and visual modalities, and diverse categories of such visual CoT. Existing interleaved datasets often fail to provide clear, meaningful connections that demonstrate when and why visual reasoning is necessary for problem-solving, while current visual CoT datasets are confined to a few domains, limiting the model's ability to learn generalizable visual CoT capabilities when faced with out-of-distribution problems.

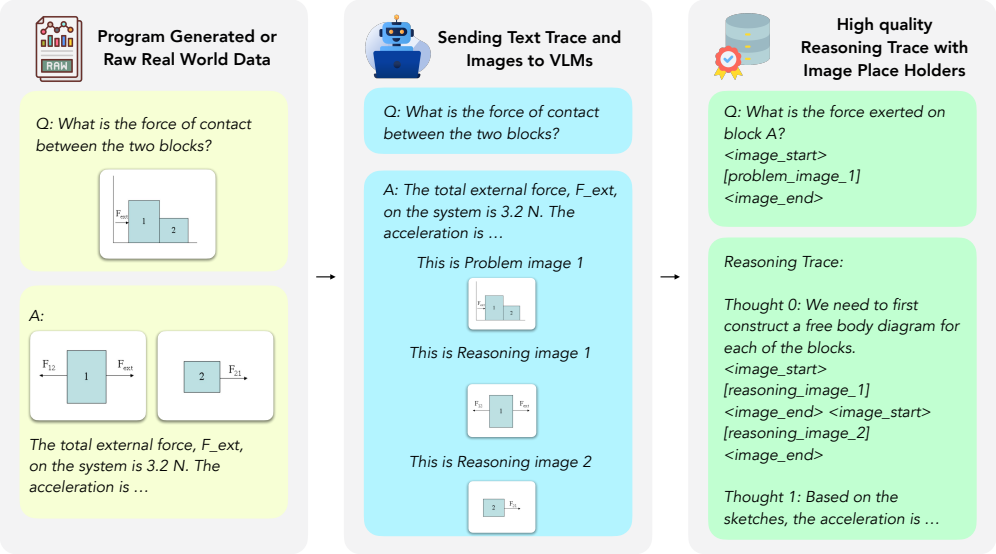


Figure 5: An overview of our data curation pipeline.

To address these requirements, we first source a diverse range of question types and domains. For real world data, we source high-quality problems from online resources such as math, physics, coding, and chess competition datasets. We then extract and clean the available raw reasoning traces that contain text and images. However, even from high quality sources, traces can still lack clear logical connections between modalities, as well as clear references to the images for automatic parsing into interleaved text and image data ready for training. For example, most geometry data uses reference labels such as "Figure x", which makes it hard to find the mapping between the actual image and the text reference. For synthetic data, we create our own examples by generating images or utilizing real images from online sources, then crafting corresponding reasoning templates. This procedure raises a clear issue, namely that we lack diversity and expressiveness in textual reasoning regarding templated data. For instance, in visual search tasks, it is crucial to elucidate the rationale behind drawing specific bounding boxes, and in chess, generating reflections and descriptions of move visualizations is key.

We address both of these issues using frontier VLMs (Gemini-2.5 and GPT-4.1) to fill in the template placeholders, enhance the reasoning traces, and complete the textual reasoning narrative. We feed both images and raw text reasoning traces into the language model and ask the language model to output pure text traces with image placeholders. We further filter out invalid cases, such as multiple image placeholders referring to the same image and unreferenced image placeholders, to ensure that the data can be automatically parsed into a training dataset.

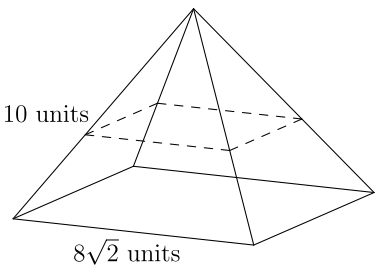
Broadening breadth and diversity of interleaved visual language reasoning dataset. Furthermore, existing multimodal rationale datasets are also limited in their breadth. The only available datasets focus on either visual search (Wu and Xie, 2024; Shao et al., 2024a) or spatial reasoning, such as maze navigation (Li et al., 2025). Such limited datasets are unlikely to enable training visual reasoning models that can generalize across domains more broadly. Visual Sketchpad (Hu et al., 2024) offers a diverse range of VLM agents to tackle a wider variety of questions. Though Sketchpad offers a powerful and significant contribution to generating visual aids, the pipeline is

not designed for collecting post-training datasets. First, the reasoning traces generated by agentic pipelines often involve tool call errors and debug information, which degrade their quality. Second, the scalability and diversity of the dataset are fundamentally constrained by the limited number of agent tool designs and the high cost, as each reasoning trace may require many API calls. To tackle these issues, we curate a total of over **182K** high-quality interleaved text and visual reasoning traces, spanning four major categories: scientific reasoning, 2D visual reasoning, 3D visual reasoning, and visual logic and strategic games. We provide the details in the section below and example traces from our dataset.

A.3 SCIENTIFIC QUESTIONS

Geometry. Geometric understanding is a core ability for multimodal models to ground reasoning over complicated mathematical tasks. Many datasets have been proposed to evaluate mathematical capabilities, including geometry. The MATH dataset (Hendrycks et al., 2021) is widely used for evaluating the mathematical performance of LLMs. Although the MATH dataset includes numerous geometry competition problems, their geometric elements are provided as plotting code rather than rendered images (see Figure 6).

Here, we provide example code for geometry sketch generation.



(a) Geometric Example in ZEBRA-COT

MATH/GEOMETRY/44

```
[asy]
import three;
size(2.5inch);
currentprojection =
orthographic(1/2,-1,1/4);
triple A = (0,0,6);
triple[] base = new triple[4];
base[0] = (-4, -4, 0);
base[1] = (4, -4, 0);
base[2] = (4, 4, 0);
base[3] = (-4, 4, 0);
triple[] mid = new triple[4];
for(int i=0; i < 4; ++i)
mid[i] = (.6*xpart(base[i]) +
.4*xpart(A), .6*ypart(base[i]) +
.4*ypart(A), .6*zpart(base[i]) +
.4*zpart(A));
for(int i=0; i < 4; ++i){
draw(A--base[I]);
draw(base[i]--base[(i+1)%4]);
draw(mid[i]--mid[(i+1)%4],
dashed);
}
label(``8√2 units",
base[0]--base[1]);
label(``10 units", base[0]--A,
2*W);
[/asy]
```

(b) Geometric Example in MATH Dataset (Hendrycks et al., 2021)

Figure 6: Comparison of the same geometric figure in our ZEBRA-COT dataset and the MATH dataset. Ours focus on multimodal reasoning and explicitly plot the geometry problem than using the text-only plotting codes.

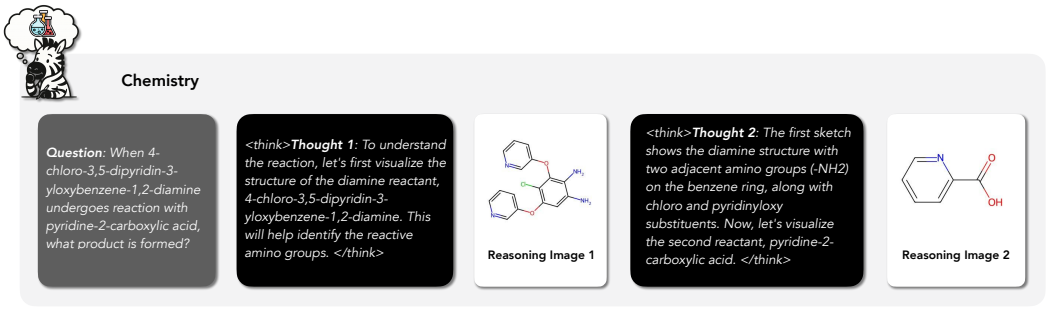
In ZEBRA-COT, we convert every piece of plotting code into figure renderings, producing both the problem diagram and its solution illustration to serve as an explicit visual reasoning chain for model training.

In total, we collect 1,061 samples from the MATH dataset's train split. Our data provides only rendered images for both the problem and solution reasoning chains, with no plotting code included. Solving these problems requires generating images to assist. The problems are not restricted to the `geometry` subcategory but also include some problems from `counting and probability`, `pre-algebra`, `pre-calculus`, etc.

Physics. A variety of physics problems benefit from sketches, such as free body diagrams for force analysis, motion diagrams for kinematics, circuit diagrams for electricity, and ray diagrams in optics. We construct samples of classical mechanics problems programmatically. Problem instances are generated from parametric Python templates (e.g., Atwood machines, inclined planes, elastic collisions, pendulums), with physically plausible parameters sampled from predefined ranges. For each sample, we render free-body diagrams, kinematic visuals, and structured CoT traces capturing the full solution process.

We also leverage openly licensed resources such as OpenStax (MIT OpenCourseWare, 2022) and MIT OCW (Moebs et al., 2016) to generate more diverse and complex physics problems, ultimately achieving scalable and legally clear dataset generation while ensuring diverse, high-quality examples.

Chemistry. Organic reaction prediction is a classic multimodal reasoning task, typically framed as symbolic input and structural output. We include a chemistry subset of 4,700 two-to-one reactions from the **USPTO-50K** dataset (Ramsundar et al., 2019), filtered for distinct reactants and single products. Each reaction trace includes three visual artifacts: individual molecular depictions of each reactant, a combined schematic of both reactants side-by-side, and the resulting product structure. Molecules are rendered with `RDKit`, and names are retrieved from PubChem when available. Text prompts use randomized templates (e.g., "What is formed by combining acetic acid and ethanol?"), and PubChem names are included when available. This visual progression helps models learn compositional chemical structure without SMILES or reaction templates.



Algorithmic problem solving. Humans naturally create visual diagrams when solving complex problems, transforming abstract concepts into spatial representations for deeper reasoning. We formalize this by interpreting coding problems through compact visual scaffolds: one or two diagrams depicting graph structure, edge weights, etc. To build traces, we run an iterative "visual sketchpad" loop: GPT-4.1 receives a prompt and returns `THOUGHT` statements plus `VIS_SPEC` blocks when sketches are needed; we render specs with `networkx`/`matplotlib`, feed images back to the model, and repeat until complete, then clean transcripts with post-processing.

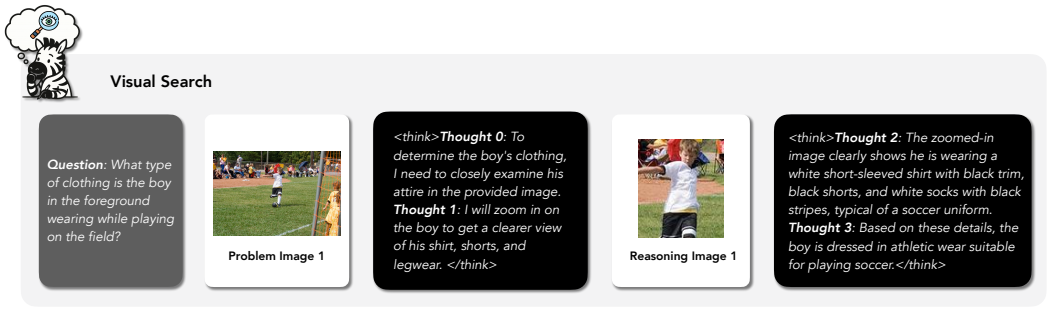
Problem samples come from competitive programming, prioritizing real-world abstractions like logistics, network routing, and flow optimization. The orchestrator produces simple visual structures emphasizing clarity over style. Each trace contains the problem prompt, 1–3 reference diagrams, and polished explanations, supporting grounded reasoning in discrete structures while mirroring how algorithms are taught. The final corpus comprises 1,200 diverse algorithm-based problems spanning competitive programming.

Graph problems. Graph algorithms are useful for large language model applications because they efficiently organize and traverse structured relationships, for example in search and retrieval applications. Methods like shortest-path and subgraph matching enable multi-step reasoning by connecting relevant concepts across knowledge graphs. Recent work by Fu et al. (2024a) shows that although LLMs can solve graph problems such as connectivity and maximum flow to some extent when a textual description of the graph is given, *multimodal* LLMs suffer when solving graph problems. This finding suggests potential for improving multimodal models' graph-understanding abilities by guiding their reasoning over images.

We create 10,000 graph problems with full reasoning traces spanning over four tasks: graph connectivity, shortest path, minimum spanning tree, and topological sort. Each task has about 2,500 samples, with one problem image and at most 19 reasoning images per sample. Each reasoning image is coupled with an explanation for the underlying algorithms, for example, Dijkstra for the shortest path, BFS for connectivity, etc.

A.4 2D Visual Reasoning

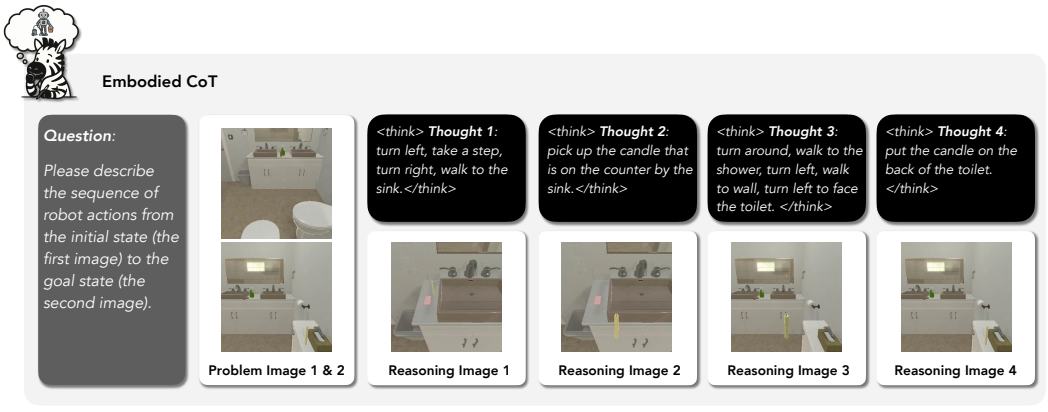
Visual search. Previous research has shown that drawing bounding boxes and zooming can improve accuracy on visual search tasks (Wu and Xie, 2024; Shao et al., 2024a). We follow such tasks by creating two types of traces, one for drawing bounding boxes and one for zooming. We use data from Shao et al. (2024a) to generate our traces covering four categories of visual search tasks: chart, text/doc, relation study, and general VQA.



Visual jigsaw. Visual jigsaw refers to filling in missing pieces of an image, as in a jigsaw puzzle. Each puzzle is constructed from an ImageNet (Deng et al., 2009) image, with 1 to 4 missing pieces of varying shapes, including rectangles and irregular regions. Each puzzle includes four multiple-choice options, where each option presents a set of candidate missing pieces. Only one set correctly matches the pieces removed from the original ImageNet image. We generate two types of visual CoT traces for solving each puzzle. In the first type, we iteratively fill in the missing patches using the pieces from each multiple-choice option and identify the one that produces a coherent image. In the second type, we imagine what the original image would look like and then select the option whose pieces best match the imagined reconstruction.

A.5 3D Visual Reasoning

Embodied planning. For embodied planning tasks, agents must *ground high-level decisions* in the evolving visual context of the environment. We reformulate the **ALFRED** (Shridhar et al., 2020) benchmark, an interactive 3D simulation environment where agents perform complex tasks based on human instructions, into an image goal-conditioned planning task.



In this new task, the model receives two images: the initial and goal states. Then the model is tasked with generating a textual description of the high-level planning steps required to transition from the initial to the goal state. To emphasize the role of visual reasoning, we require the generated descriptions to be detailed and step-by-step (e.g., *"turn and go to the TV; pick up the bowl that is on the TV stand in front of the TV; with the bowl in hand..."*) rather than brief summaries (e.g., *"move bowl to coffee table"*), which can often be produced through shortcut reasoning without capturing intermediate visual steps.

We compile the entire training set, as well as the seen and unseen validation sets from ALFRED, resulting in a total of 7,080 examples spanning diverse visual reasoning trajectories. When multiple textual reasoning annotations exist for a single visual trajectory, we include all of them, resulting in 22,666 textual reasoning traces.

Robot planning. While low-level manipulation may rely on reactive control, continuous planning for complex tasks often requires *high-level visual guidance*, making visual CoT essential for bridging perception and long-horizon decision-making in robot planning. Similarly, we reformulate **RoboMIND** (Wu et al., 2024), a multi-embodiment dataset of real-world robot manipulation, into an image goal-conditioned planning task. In this setting, a model is provided with the initial and goal states images, along with a textual description of the robot setup (e.g., AgileX (AgileX Robotics, 2023), Franka (Franka Emika GmbH, 2018), or UR5e (Universal Robots A/S, 2018)), and is tasked with generating a detailed textual plan outlining the high-level steps required to transition from the initial to the goal state.

Unlike embodied planning tasks that often involve partial observability and require agents to infer unobserved states, this robot planning task is fully observable. Therefore, the challenge lies not in imagining the visual trajectory but in articulating precise movements for each arm or gripper to accomplish the task (e.g., *"[left] move towards the oven door and [right] grab the corn."*).

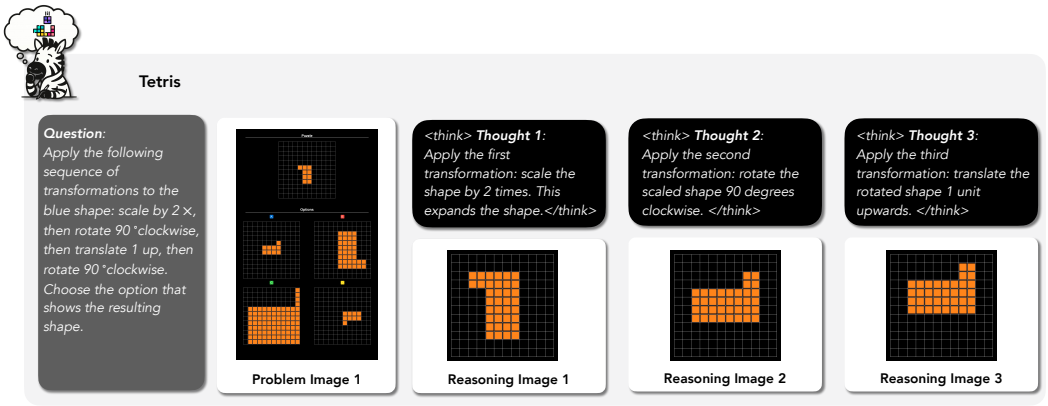
To control degrees of freedom, we exclude the humanoid robot examples from the original RoboMIND dataset, focusing solely on tasks involving robotic arms. This results in a curated subset of 6,945 robot planning tasks, each annotated with human-generated high-level actions that serve as visual reasoning trajectories.

3D multi-hop objects counting. A core aspect of human visual-spatial reasoning is understanding transformations and imagining scenes from different viewpoints. For this task, our setup follows a structure similar to that of Johnson et al. (2017), using 10 predefined shape types (e.g., sphere, cylinder, donut) in various colors. At each step, we randomly apply one of three operations: remove all instances of an attribute (e.g., all red objects), remove a subset (e.g., 5 red objects), or add new objects (e.g., 2 blue prisms, 1 red sphere). We then create questions that ask about the quantity of specific attributes or what objects are left in the field. To increase difficulty, the initial scenes are rendered from varying viewpoints (front, back, left, right), where some objects may be partially occluded by those in front. The first visual reasoning step involves generating a top-down 45° view to reconstruct the full scene, allowing the model to see potentially blocked objects. The subsequent visual sketches correspond to each transformation step in the instruction. We also improve upon the data from Johnson et al. (2017) by adding in different materials, backgrounds, and floor designs.

A.6 Visual Logic and Strategic Games

Visual logic puzzles. Humans approach logic puzzles such as Tetris, Raven's Progressive Matrices (RPM, Zhang et al., 2019) , and the Abstraction & Reasoning Corpus (ARC-AGI, Chollet, 2019; Chollet et al., 2024) primarily through visuospatial reasoning: we see how pieces combine, transform, or complete a pattern before committing to an answer. These logic games rely heavily on visuospatial working memory, which is correlated with general intelligence level (Lau-Zhu et al., 2017; de Winter et al., 2023).

To enhance models with such cognitive ability, we include the following tasks. For *Tetris*, we collect three types of tasks: a) shape assembly: given a silhouette and candidate tetromino sets, select the one that perfectly tiles the shape; b) grid completion: fill a partially occupied grid using a specified set of tetrominoes; c) spatial transformation: apply a sequence of geometric operations (translate, rotate, mirror, scale) to an irregular shape in the grids. The visual CoT involves visualizing each transformation step. For *RPM* (IQ matrix), we include three types from Zhang et al. (2019) that



involve compositional reasoning. The reasoning trace identifies visual patterns for each compositional component across rows or columns. For *ARC-AGI*, while prior models often rely on textual reasoning, humans typically solve these tasks through visual pattern recognition. To better align with human strategies, we construct two types of visual CoT. The first begins with matrix representations of the training examples and test input; the reasoning trace first visualizes the training examples, the test input, and finally the predicted output. The second type directly uses visual representations in the task instruction, thus the model only has to generate a visual sketch of the predicted output as part of its reasoning process. For all data, we use VLM to generate accompanying textual descriptions to enrich interleaved text-image rationales.

Mazes. Mazes serve as a canonical testbed for visual CoT reasoning, bridging low-level perception with high-level symbolic search. Unlike purely pixel-based 2D visual tasks such as visual search and visual jigsaw, mazes possess explicit graph structure yet remain visually intuitive, letting us disentangle vision errors from planning errors.

We adopt the `maze-dataset` library to procedurally generate thousands of grid mazes with diverse topologies (lattice type, branch factor, loop density).[1] Each instance is exported in two complementary formats: a) `m.as_pixels()`, an RGB raster that encodes walls, free cells, start ■, and goal ■, suitable for visual perception; b) `MazePlot`, a vector overlay that can superimpose solution paths, candidate trajectories, heat-maps, or landmark nodes for human-readable walk-throughs. To increase maze diversity, we also use OpenAI Gym's `FrozenLake-v1` environment (Brockman et al., 2016) .

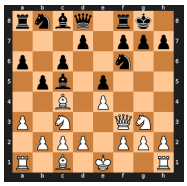
We evaluate a broad spectrum of spatial reasoning skills across multiple question types: *I. topological analysis* (e.g., counting isolated regions, identifying connected components under 4- or 8-connectivity, finding the largest connected area), *II. pathfinding* (e.g., determining reachable endpoints, computing shortest paths, enumerating all optimal routes), *III. navigation planning* (e.g., selecting correct paths from alternatives, calculating minimal moves to reach targets), and *IV. coverage problems* (e.g., visiting all marked locations, identifying the farthest reachable position). This diverse task suite goes beyond simple start-to-goal navigation, encompassing the full range of spatial reasoning strategies that humans use to interpret complex environments. We also introduce varying complexity of the matrix, including different maze side lengths ranging from $(5, 15)$, different branching factors b, loop probability ℓ, and number of distractor endpoints k. Larger n exponentially increases the search space, while higher b and ℓ degrade heuristic admissibility. Both of those require genuine planning rather than rote memorization.

Chess.

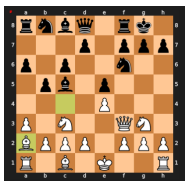
Strategic planning in chess involves simulating multiple futures and selecting moves that maximize long-term advantage. To support counterfactual reasoning, we construct a dataset of mid-game positions from rated Lichess games [2], each with structured visual traces. Given a position, `Stockfish`

[1] `maze-dataset` supports recursive-backtracker, randomized Prim, Wilson, and Kruskal generators; see (Ivanitskiy et al., 2023).

[2] `https://lichess.org/`



What's White's best move? Options: A: Ba2, B: Na4, C: Qf5, D: Bb3.



(A) **Ba2**: Safe position supports central pawns

(B) **Na4**: Poorly placed weak attack on b6

(C) **Qf5**: Exposed queen vulnerable to g6

(D) **Bb3**: Vulnerable position weaker than Ba2

Figure 7: Traces showing reasoning for each move option. Option A (Ba2) is evaluated as strongest, providing safe bishop placement while supporting potential central pawn advances.

identifies the optimal move, and three alternates are sampled randomly from legal moves. Each candidate is visualized independently for comparative evaluation. By rendering possibilities in isolation, move consequences, tempo gain, structural weakening, and tactical motifs become legible, enabling better strategic reasoning. Traces are formatted as multiple-choice tasks with visual sketches, encouraging tactical awareness and pattern recognition. Postprocessing with Gemini 2.5 Flash refines traces into coherent multimodal reasoning sequences for short and long-horizon planning, yielding 11,500 chess traces across diverse positions and hypothetical move states.

Connect 4. We also include 2,100 Connect-Four traces that teach short-horizon grid planning. Each starts from a mid-game position obtained after 4–20 random moves; a depth-4 α–β minimax (center-control, open-three heuristic) then plays the forced win. Every drop is rendered on a 7×6 board with a glowing overlay, and an LLM condenses the raw log into a clear, step-by-step "How does Red win?" narrative pairing text and visuals.

Checkers. Our checkers traces, initiated from randomized mid-game boards and continued through depth-4 minimax, are designed to capture key tactical motifs such as forced captures, multi-jump chains, and king-row advancement, providing dense supervision for spatially grounded decision making. To ensure data quality, we apply rule-based validators that discard invalid traces. Final traces are passed through a language model to synthesize coherent visual reasoning aligned with *turn-based planning*, ending with 2,800 full traces.

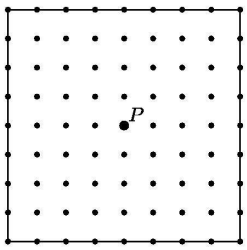
Ciphers. Classical encryption schemes convert symbolic rules into spatial transformations, enabling visual reasoning over grids and coordinates. We generate examples of *Scytale*, *Polybius*, *Rail Fence* and *Playfair* ciphers, each with multimodal traces showing encoding steps. Visual sketches highlight relevant regions such as column positions, grid lookups, or digraph geometry, while text describes applied rules (e.g., *"Letter 'P' goes on the second rail," "'A' is at coordinates (1, 1)."*) Early steps use visuals, later steps use language, mirroring real cryptanalysis. The 6,600 traces align symbolic manipulation with visual structure.

B EXTRA BAGEL ZEBRA COT GENERATED VISUAL COT

Visual CoT Example: EMMA

Prompt:

There are 81 grid points (uniformly spaced) in the square shown in the diagram below, including the points on the edges. Point P is the center of the square. Given that point Q is randomly chosen from among the other 80 points, what is the probability that line PQ is a line of symmetry for the square?

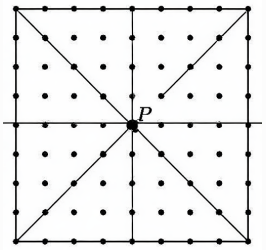


Visual CoT:

<think>
The problem asks for the probability that a randomly chosen point Q from the 80 points other than the center P results in the line PQ being a line of symmetry for the square. We need to determine the number of such points Q and divide by the total number of possible points (80).

First, let's visualize the grid and the center point P. The grid has 9 points along each side, so there are 80 points in total (excluding P). A line of symmetry for a square passes through the center P and divides the square into two congruent halves. For PQ to be a line of symmetry, Q must be the reflection of P across this line. This means Q must be on the grid line that forms a line of symmetry with P.

Let's consider the lines of symmetry for the square. A square has 4 lines of symmetry: 2 diagonals, the vertical line through the center, and the horizontal line through the center. Let's visualize these lines.
</think>

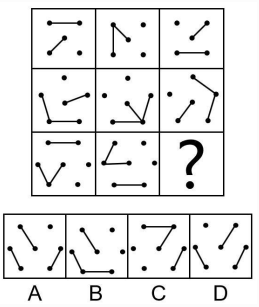


[Visual Thought]

Visual CoT Example: VisuLogic

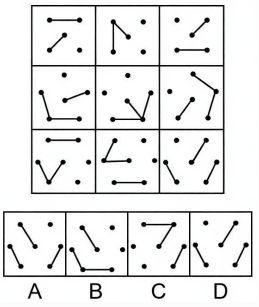
Prompt:

Solve the complex visual logical reasoning problem through step-by-step reasoning.



Visual CoT:

<think>
Observe the grid to identify patterns in the shapes and their components. The grid is divided into 3x3 cells. Each cell contains two distinct shapes: a line segment and a dot. I will analyze the patterns for the line segment and the dot separately. For the line segment, the pattern is: (Top Left, Top Right) = (Bottom Left, Bottom Right). For the dot, the pattern is: (Top Left, Top Right) = (Bottom Left, Bottom Right). Now, I will apply these patterns to the third row and third column to find the missing shape. The missing shape in the third row and third column should have a line segment like the one in the third row, third column (which is the same as the third row, second column line segment). The missing shape in the third row and third column should also have a dot like the one in the third row, third column (which is the same as the third row, second column dot). Combining these, the missing shape should be a line segment from the third row, second column and a dot from the third row, second column.
</think>

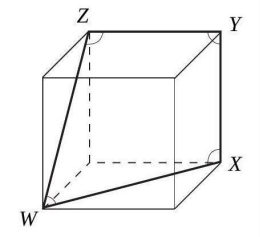


[Visual Thought]

Visual CoT Example: EMMA

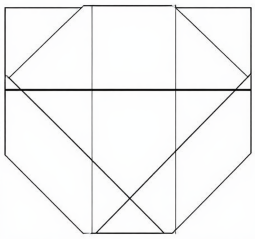
Prompt:

The picture shows a cube with four marked angles: $\angle WXY$, $\angle XYZ$, $\angle YZW$, and $\angle ZWX$. What is the sum of these angles?



Visual CoT:

<think>
The problem asks for the sum of four specific angles in a cube. The angles are $\angle WXY$, $\angle XYZ$, $\angle YZW$, and $\angle ZWX$. These angles are formed by the edges of the cube meeting at vertices X, Y, Z, W.



[Visual Thought]

In a cube, each vertex is formed by three edges that are mutually perpendicular. This means that at each vertex, the three edges meet to form right angles.
Let's consider vertex X. The edges WX, XY, and XZ meet at vertex X. Since the edges are perpendicular, the angle $\angle WXY = 90°$.
Similarly, we can analyze the other vertices:

- At vertex Y: edges XY, YZ are perpendicular, so $\angle XYZ = 90°$
- At vertex Z: edges YZ, ZW are perpendicular, so $\angle YZW = 90°$
- At vertex W: edges ZW, WX are perpendicular, so $\angle ZWX = 90°$

We have identified the measures of all four angles: $\angle WXY = 90°$, $\angle XYZ = 90°$, $\angle YZW = 90°$, $\angle ZWX = 90°$
To find the sum of these angles, we add their measures:

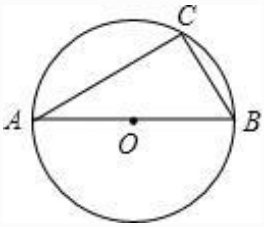
$$90° + 90° + 90° + 90° = 360°$$

The sum of the angles $\angle WXY$, $\angle XYZ$, $\angle YZW$, and $\angle ZWX$ is $\mathbf{360}°$.
</think>

Visual CoT Example: MathVista

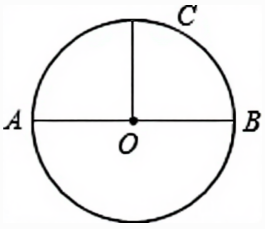
Prompt:

Question: As shown in the figure, AB is the diameter of $\odot O$, and point C is on $\odot O$. If $\angle A = 40.0$, then the degree of $\angle B$ is?



Visual CoT:

<think>
First, let's analyze the geometry of the problem. Since AB is the diameter of the circle, any angle inscribed in the semicircle formed by AB will be a right angle. Thus, angle ACB is a right angle, measuring 90 degrees. Now, let's draw an auxiliary line connecting point O (the center of the circle) to point C. This line segment OC is a crucial part of our reasoning. The line segment OC can be labeled as shown in the image.



[Visual Thought]

Since AB is the diameter of the circle, O is the center. Therefore, AO and BO are radii of the circle, making them equal in length. By the properties of an isosceles triangle (AO = BO), and having an angle of 90 degrees at C (i.e., angle ACB), we can deduce that triangle ABC is an isosceles right-angled triangle. This means that angle A is equal to angle CBA, and since angle ACB is 90 degrees, the two other angles must add up to 90 degrees. Given that angle A is 40 degrees, angle B must be 50 degrees. Therefore, angle B is 50 degrees.
</think>

Visual CoT Example: BLINK

Prompt:

How many kids are sitting on the bench in the image?

Visual CoT:

<think>

[Visual Thought]

Let's count the number of kids sitting on the bench in the image. To get a clearer view of the kids on the bench, I will zoom in on the relevant area. The zoomed-in image clearly shows four children sitting on the bench. Based on this visual evidence, the number of kids on the bench is four.
</think>

C ANOLE-ZEBRA PERFORMANCE BREAKDOWN

Split	Anole	Anole-Zebra-CoT (Ours)
Overall	12.80	**15.03**
Chemistry	12.84	**15.48**
Coding	9.75	**16.31**
Math	13.12	**14.35**
Physics	**21.79**	10.90

Table 4: EMMA: breakdown by subject (%).

Subtask	Anole	Anole-Zebra-CoT (Ours)
Overall	22.80	**24.90**
Scientific reasoning	30.33	**32.79**
Textbook question answering	**36.08**	29.75
Numeric commonsense	16.67	**17.36**
Arithmetic reasoning	15.58	**18.98**
Visual question answering	24.58	**29.61**
Geometry reasoning	20.50	**23.01**
Algebraic reasoning	**25.27**	24.56
Geometry problem solving	21.15	**24.04**
Math word problem	9.14	**12.37**
Logical reasoning	**29.73**	10.81
Figure question answering	24.54	**28.25**
Statistical reasoning	20.27	**26.58**

Table 5: MathVista: breakdown by subtask for base vs. our model (%).

Subtask	Anole	Anole-Zebra-CoT (Ours)
Overall	8.50	**21.80**
Quantitative reasoning	8.78	**21.81**
Spatial reasoning	8.23	**22.08**
Positional reasoning	8.82	**19.85**
Attribute reasoning	9.76	**25.61**
Stylistic reasoning	10.00	**24.44**
Other	5.56	**18.52**

Table 6: Visual Logic: breakdown by subtask (%).

Category	Anole	Anole-Zebra-CoT (Ours)
Overall	26.46	**31.25**
Art Style	19.66	**35.04**
Counting	**19.17**	15.00
Forensic detection	0.00	**20.45**
Functional correspondence	17.69	**22.31**
IQ test	**26.67**	23.33
Jigsaw	11.33	**39.33**
Multi-view reasoning	**48.12**	21.05
Object localization	**50.82**	45.90
Relative depth	38.71	**41.94**
Relative reflectance	**29.10**	27.61
Semantic correspondence	**19.42**	17.99
Spatial relation	41.26	**57.34**
Visual correspondence	21.51	**26.16**
Visual similarity	30.37	**44.44**

Table 7: Blink: breakdown by category (%).

D BAGEL PERFORMANCE ANALYSIS

We evaluate our Bagel model trained on ZEBRA-COT across several benchmarks but did not observe substantial improvements over the original model, where the original generates pure text responses. In fact, we even saw slight performance drops on some tasks such as MathVista. A detailed analysis revealed a likely cause of this decline. The Bagel model employs two visual encoders: a ViT-based understanding encoder and a VAE-based generation encoder. For generated images, the model often produces hallucinations. For example, when instructed to remove all red balls from a scene, the generated image may also remove yellow balls. When this corrupted image is passed back into the ViT encoder, the representation correctly reflects that both red and yellow balls are missing, leading the model to reason over inaccurate visual information, ultimately reducing accuracy. Instead generating pure text responses avoids such image generation hallucinations.

E SCAFFOLDING RESULTS BREAKDOWN

Chess					
Model	Q (%)	1MT (%)	2MT (%)	Δ1MT (%)	Δ2MT (%)
Claude-4 Sonnet	32.95	57.95	67.05	25.00	34.09
Gemini-2.5 Pro	15.07	39.73	39.73	24.66	24.66
GPT-5	45.78	62.65	61.45	16.87	15.66
Graph					
Model	Q (%)	1MT (%)	2MT (%)	Δ1MT (%)	Δ2MT (%)
Claude-4 Sonnet	8.11	20.72	22.52	12.61	14.41
Gemini-2.5 Pro	1.90	11.43	20.95	9.52	19.05
GPT-5	1.74	14.78	22.61	13.04	20.87
2D Visual Jigsaw					
Model	Q (%)	1MT (%)	2MT (%)	Δ1MT (%)	Δ2MT (%)
Claude-4 Sonnet	21.74	36.23	62.32	14.49	40.58
Gemini-2.5 Pro	34.38	56.25	59.38	21.88	25.00
GPT-5	62.86	77.14	85.71	14.29	22.86
Maze					
Model	Q (%)	1MT (%)	2MT (%)	Δ1MT (%)	Δ2MT (%)
Claude-4 Sonnet	35.06	58.44	94.81	23.38	59.74
Gemini-2.5 Pro	59.70	85.07	97.01	25.37	37.31
GPT-5	63.01	86.30	97.26	23.29	34.25
3D Multi-Hop Counting					
Model	Q (%)	1MT (%)	2MT (%)	Δ1MT (%)	Δ2MT (%)
Claude-4 Sonnet	59.68	67.74	74.19	8.06	14.52
Gemini-2.5 Pro	45.95	48.65	51.35	2.70	5.41
GPT-5	72.58	74.19	77.42	1.61	4.84
Tetris					
Model	Q (%)	1MT (%)	2MT (%)	Δ1MT (%)	Δ2MT (%)
Claude-4 Sonnet	18.87	39.62	45.28	20.75	26.42
Gemini-2.5 Pro	8.57	25.71	31.43	17.14	22.86
GPT-5	30.77	50.00	59.62	19.23	28.85

Table 8: Scaffolding evaluation results across task domains. Q: zero-shot question-only; 1MT: question with first multimodal reasoning step; 2MT: question with first two multimodal reasoning steps. Δ columns show absolute improvement over baseline (Q).

Chess					
Model	Q (%)	1TT (%)	2TT (%)	Δ1TT (%)	Δ2TT (%)
Claude-4 Sonnet	32.95	42.05	40.91	9.10	7.96
Gemini-2.5 Pro	15.07	13.70	19.86	-1.37	4.79
GPT-5	45.78	51.81	62.65	6.03	16.87
Graph					
Model	Q (%)	1TT (%)	2TT (%)	Δ1TT (%)	Δ2TT (%)
Claude-4 Sonnet	8.11	20.72	15.32	12.61	7.21
Gemini-2.5 Pro	1.90	5.71	5.71	3.81	3.81
GPT-5	1.74	11.30	19.13	9.56	17.39
2D Visual Jigsaw					
Model	Q (%)	1TT (%)	2TT (%)	Δ1TT (%)	Δ2TT (%)
Claude-4 Sonnet	21.74	39.13	30.43	17.39	8.69
Gemini-2.5 Pro	34.38	24.22	25.00	-10.16	-9.38
GPT-5	62.86	68.57	71.43	5.71	8.57
Maze					
Model	Q (%)	1TT (%)	2TT (%)	Δ1TT (%)	Δ2TT (%)
Claude-4 Sonnet	35.06	49.35	55.84	14.29	20.78
Gemini-2.5 Pro	59.70	23.29	39.73	-36.41	-19.97
GPT-5	63.01	63.01	75.34	0.00	12.33
3D Multi-Hop Counting					
Model	Q (%)	1TT (%)	2TT (%)	Δ1TT (%)	Δ2TT (%)
Claude-4 Sonnet	59.68	69.35	69.35	9.67	9.67
Gemini-2.5 Pro	45.95	54.84	56.45	8.89	10.50
GPT-5	72.58	72.58	74.19	0.00	1.61
Tetris					
Model	Q (%)	1TT (%)	2TT (%)	Δ1TT (%)	Δ2TT (%)
Claude-4 Sonnet	18.87	26.42	32.08	7.55	13.21
Gemini-2.5 Pro	8.57	11.54	7.69	2.97	-0.88
GPT-5	30.77	28.85	42.31	-1.92	11.54

Table 9: Text-only CoT evaluation results across task domains. Q: zero-shot question; 1TT: first text reasoning step; 2TT: first two text reasoning steps. Δ columns show absolute improvement over Q.

F PROMPT TEMPLATES

F.1 PROMPT FOR ENHANCING RAW REASONING TRACES FOR ONLINE AND AGENTIC DATA

Prompt Template 1

```
You are an expert in creating clean and logically coherent
 ↪  multimodal chain of thought traces. Your task is to
 ↪  analyze
and comprehend a raw reasoning trace with interleaved text
 ↪  and images, then transform it into a clean, step-by-step
 ↪  multimodal
reasoning trace that correctly solves the original problem.

========================  INPUT  ========================
1. Problem & Noisy Trace: A raw interleaved text and image
 ↪  reasoning trace. Images in this trace are represented by
 ↪  placeholders:
   - `[problem_image_X]` for original problem images (e.g.,
    ↪  `[problem_image_1]`, `[problem_image_2]`)
   - `[reasoning_image_X]` for images generated during
    ↪  reasoning (e.g., `[reasoning_image_1]`,
    ↪  `[reasoning_image_2]`)
2. Image Data: The actual image data corresponding to the
 ↪  placeholders, provided separately.

=====================  Your Task  =================
Generate a clean, logical multimodal reasoning trace as
 ↪  **plain text** that represents the *ideal* reasoning
 ↪  process to solve the problem.

====================  OUTPUT FORMAT  ==================
You MUST generate the formatted reasoning trace with the
 ↪  following structure:

QUESTION:
<The original problem statement with text and image
 ↪  placeholders: <image_start>[problem_image_1]<image_end>,
 ↪  <image_start>[problem_image_2]<image_end>, etc. Stay as
 ↪  close to the original problem statement as possible but
 ↪  remove noise to ensure clarity>

REASONING TRACE:
THOUGHT 0: <Clear description of initial reasoning step that
 ↪  identifies key elements of the problem>
THOUGHT 1: <Next reasoning step, often explaining why an
 ↪  image will be created>
<image_start>[reasoning_image_1]<image_end>
THOUGHT 2: <Further reasoning step based on the image,
 ↪  explaining insights gained>
<image_start>[reasoning_image_2]<image_end>
// Additional thoughts and images as needed
<image_start>[reasoning_image_X]<image_end>
THOUGHT N: <Final reasoning step before the answer,
 ↪  summarizing key insights>

FINAL ANSWER:
```

```
<The final calculated answer based on the reasoning>

====================  Guidelines  ================

1. Enhancing Original Trace Rather than Generating New Trace:
  - Instead of generating a new trace, your task is to
   ↪  enhance the original trace (which is a correct trace
   ↪  but rather concise and lacks coherent multimodal
   ↪  reasoning) by adding more details and explanations, see
   ↪  the following sections of guidelines for more details.
  - You MUST use all the images provided in the original
   ↪  trace.
  - You should use the original trace as a reference rather
   ↪  than copying it verbatim.

2. Multimodal Reasoning Flow:
   - Develop a coherent, step-by-step chain of thought that
    ↪  seamlessly integrates textual and visual reasoning.
   - Clearly explain the necessity of generating a sketch /
    ↪  visual thought / image before introducing its
    ↪  placeholder.
   - After each image placeholder, describe the insights
    ↪  gained from the sketch / visual thought / image, and
    ↪  how it contributes to advancing the solution.
   - Ensure each step logically builds on the previous ones,
    ↪  especially between text reasoning and visual reasoning
   steps.

3. Image Placeholders and References:
   - Use placeholder tags ONLY when you want to actually
    ↪  insert/show/generate an image in your trace. When
    ↪  doing so, write the corresponding placeholder tag
    ↪  exactly as shown, including the <image_start> and
    ↪  <image_end> tags.
   - Each unique image in the original problem and the
    ↪  reasoning trace should be represented by a unique
    ↪  placeholder tag, and each unique placeholder tag
    ↪  should only show up once in the trace.
   - When referring to images in your explanations, use
    ↪  natural language descriptions (e.g., "the diagram in
    ↪  the question", "the first sketch", "the visual thought
    ↪  X I created") instead of using placeholder tags. This
    ↪  is important because it helps us to parse into
    ↪  interleaved text and image sequences.
   - For images from the original problem, use:
    ↪  <image_start>[problem_image_X]<image_end>
   - For sketches or visuals generated during reasoning, use:
    ↪  <image_start>[reasoning_image_X]<image_end>

4. Narrative Style:
   - Remove irrelevant technical details such as debugging
    ↪  info, code snippets, and LaTeX package imports.
   - Eliminate verbose language that do not contribute to
    ↪  solving the problem.
   - Focus on the essential reasoning path that leads to the
    ↪  correct solution, using concise and clear language to
    ↪  describe the overall reasoning process.
```

F.2 Prompt for Enhancing Program Generated Template Data

Prompt Template 1

```
You are an expert in enhancing multimodal reasoning traces.
 ↪  Your task is to transform a template reasoning trace into
 ↪  a diverse multimodal reasoning trace that correctly
 ↪  solves the problem, while staying close to the original
 ↪  template and final answer.

======================  INPUT  ======================
1. Problem & Template Trace: A template with interleaved text
 ↪  and image placeholders:
   - `[problem_image_X]` for original problem images (e.g.,
    ↪  `[problem_image_1]`)
   - `[reasoning_image_X]` for images generated during
    ↪  reasoning (e.g., `[reasoning_image_1]`)
2. Image Data: The actual image data corresponding to the
 ↪  placeholders, provided separately.

====================  Your Task  =================
Generate a concise multimodal reasoning trace as **plain
 ↪  text**.

====================  OUTPUT FORMAT  ==================
You MUST generate the formatted reasoning trace with the
 ↪  following structure:

QUESTION:
<Rewrite the problem statement in your own words while
 ↪  maintaining all key information. Do not change key
 ↪  information. Include image placeholders:
 ↪  <image_start>[problem_image_1]<image_end>,
 ↪  <image_start>[problem_image_2]<image_end>, etc.>

REASONING TRACE:
THOUGHT 0: <Identify key elements of the problem>
THOUGHT 1: <Explain reasoning step, often why an image /
 ↪  sketch / visual thought is needed>
<image_start>[reasoning_image_1]<image_end>
THOUGHT 2: <Explain insights from the image>
<image_start>[reasoning_image_2]<image_end>
// Additional thoughts and images as needed
<image_start>[reasoning_image_X]<image_end>
THOUGHT N: <Summarize key insights before answer>

FINAL ANSWER:
<The original final answer in the template, do not change it>

====================  Guidelines  =================

1. Diversifying the Template:
   - Rewrite the problem statement and reasoning steps in
    ↪  your own words while preserving all key information.
   - Avoid deviating from the original template reasoning
    ↪  structure. Your job is to diversify the text of the
    ↪  original trace, not the logic.
```

```
   - Vary the language and phrasing to avoid repetitive
    ↪ patterns.
   - You MUST use all the images provided in the original
    ↪ trace.
   - You MUST keep the original final answer.
   - Maintain the original template's core reasoning
    ↪ structure and rationale while introducing textual
    ↪ reasoning refinements rather than substantial changes
    ↪ to the logical flow.

2. Multimodal Reasoning Flow:
   - Develop a coherent, step-by-step chain of thought that
    ↪ seamlessly integrates textual and visual reasoning.
   - Clearly explain the necessity of generating a sketch /
    ↪ visual thought / image before introducing its
    ↪ placeholder.
   - After each image placeholder, describe the insights
    ↪ gained from the sketch / visual thought / image, and
    ↪ how it contributes to advancing the solution.
   - Ensure each step logically builds on the previous ones,
    ↪ especially between text reasoning and visual reasoning
    ↪ steps.

3. Image Placeholders and References:
   - Use placeholder tags ONLY when you want to actually
    ↪ insert/show/generate an image in your trace. When
    ↪ doing so, write the corresponding placeholder tag
    ↪ exactly as shown, including the <image_start> and
    ↪ <image_end> tags.
   - Each unique image in the original problem and the
    ↪ reasoning trace should be represented by a unique
    ↪ placeholder tag, and each unique placeholder tag
    ↪ should only show up once in the trace.
   - When referring to images in your explanations, use
    ↪ natural language descriptions (e.g., "the diagram in
    ↪ the question", "the first sketch", "the visual thought
    ↪ X I created") instead of using placeholder tags. This
    ↪ is important because it helps us to parse into
    ↪ interleaved text and image sequences.
   - For images from the original problem, use:
    ↪ <image_start>[problem_image_X]<image_end>
   - For sketches or visuals generated during reasoning, use:
    ↪ <image_start>[reasoning_image_X]<image_end>
```

F.3 Prompt for Algorithmic Problems

Prompt Template 2

```
You are an expert in mathematical problem solving,
 ↪ algorithmic reasoning, visual explanation, and creating
 ↪ multimodal reasoning traces.

---
1. STRICT VISUALIZATION POLICY (IMPORTANT):
```

```
You are only allowed to produce at most 3 [VIS_SPEC]
 ↪  visualizations, and they must all appear at the very
 ↪  beginning of your reasoning (within the first 3--4
 ↪  thoughts). You may only use the following types for these
 ↪  visualizations:
    - graph
    - flow_network
    - tree_from_dict
    - tree_from_root
    - grid

After these initial visualizations, you must do all further
 ↪  reasoning purely mentally/textually or with
 ↪  pseudocode--NO MORE [VIS_SPEC] blocks are allowed after
 ↪  the first 3. Any attempt to include more than 3
 ↪  visualizations or use a disallowed type will be ignored.
The visual reasoning should only be used to understand the
 ↪  setup of the question - humans visualize at the beginning
 ↪  to ``set the board.'' The actual problem solving is done
 ↪  purely textually.

**General Rules:**
- Interleave THOUGHT steps and [VIS_SPEC] image requests.
- Your final reasoned solution must match the logic of the
 ↪  given solution code.
- Prefix THOUGHT 0 with REASONING TRACE in the previous line.
- Prefix each reasoning step with ``THOUGHT n:'' (n starts at
 ↪  0, less than 50 words each).
- Max 3 [VIS_SPEC] blocks, all within the first 3--4
 ↪  thoughts.
  - Diagram #1: raw structural sketch (graph topology, blank
   ↪  grid, etc.).
  - Diagram #2--3: showcase pivotal elements if helpful.
- **Internal self-check (no output):** ``Would a human
 ↪  scribble this as a quick setup sketch?'' If the answer is
 ↪  no, **do not** emit a VIS_SPEC.
- Strictly do not regenerate the same image - simply refer to
 ↪  the previous images in text if needed.
- Max of 10 thoughts.
- Every visualization request **must** use a minimal
 ↪  [VIS_SPEC] block with the correct type specified. Do not
 ↪  use any other format.
- Do **not** include file names, imports, or drawing code.
 ↪  The orchestrator will handle image generation.
- If you cannot meaningfully visualize or correctly visualize
 ↪  a thought using the provided tools and inputs, then do
 ↪  not generate an image.
- Images are meant to be simple and visually cohesive - do
 ↪  not make grandiose images with titles and axis - it's
 ↪  simply for a baseline understanding of the question.
- The first line of the trace should be QUESTION: followed by
 ↪  a detailed in depth recap of the problem, specifying all
 ↪  the important aspects, without mentioning the solution.


2. Validity Rules:
```

```
- All [VIS_SPEC] parameters must be valid, fully-formed
 ↪  Python literals.
- For [VIS_SPEC] type "grid", the values must be a valid
 ↪  Python list of lists with exactly rows rows and cols
 ↪  columns (or a flat list of length rows * cols), and each
 ↪  value should be a number or string.
- For type graph, tree_from_dict, tree_from_root, and
 ↪  similar, node and edge labels may be strings or integers,
 ↪  but all structures must be valid Python literals.
- Never output incomplete or empty lists/arrays/dicts in
 ↪  [VIS_SPEC] blocks. All lists must be fully closed and
 ↪  contain at least one value, unless an empty structure is
 ↪  explicitly required by the problem.
- Do not use variable names, symbolic labels, ellipses, or
 ↪  placeholders (e.g., a1, x, \ldots, an) anywhere in the
 ↪  [VIS_SPEC].

---

**[VIS_SPEC] Reference Examples: Your blocks must follow the
 ↪  same format as these.**

[VIS_SPEC]
type: graph
nodes: [A,B,C]
edges: [(A,B),(B,C)]
[/VIS_SPEC]

[VIS_SPEC]
type: flow_network
nodes: [A,B,C]
edges: [(A,B),(B,C)]
flows (optional): {(A,B): 2, (B,C): 1}
capacities (optional): {(A,B): 3, (B,C): 2}
[/VIS_SPEC]

\ldots
\ldots
\ldots

3. Reflection step immediately after each VIS_SPEC
   - Write a new THOUGHT that:
     a. Describes what you see in the previous generated
      ↪  `reasoning_image_N.png`.
     b. Explains how it informs your next reasoning move.

4. FINAL ANSWER
   - After all reasoning, output ``FINAL ANSWER:'' and your
    ↪  concise solution (pseudocode is sufficient)

5. Formatting and Output Requirements
   - Everything must be plain text with only the full
    ↪  QUESTION (just the problem itself, not the name of the
    ↪  problem), FINAL ANSWER, REASONING TRACE marker,
    ↪  THOUGHT lines and VIS_SPEC markers.
```

G IMPACT STATEMENT

All data sourced in this work were either publicly available under open licenses or generated synthetically. We ensured that all original content and assets used in the dataset creation process respect copyright and licensing terms. No human subjects were involved, and we do not foresee any direct harm to individuals or communities as a result of this work. The dataset is intended solely for academic research to improve multimodal reasoning capabilities in AI systems.

H LICENSES

We list the licenses involved in this work as follows,

- `Anole-7B` model is under *Chameleon Research License*.
- `BAGEL-7B-MoT` model is licensed under the *Apache 2.0 license*. It is finetuned from *Qwen2.5-7B-Instruct* and *siglip-so400m-14-384-flash-attn2* model, and uses the *FLUX.1-schnell VAE model*, all under *Apache 2.0*.
- `ImageNet` dataset in under *BSD 3* license.
- `Visual CoT` dataset is licensed under *CC BY 4.0*
- `MATH` dataset (Hendrycks et al., 2021) is under *MIT License*.
- `OpenStax` Physics books are license under *CC BY 4.0*.
- `MIT OCW` Physics lecture notes under *CC BY 4.0*.
- `Maze` datasets is licensed under *CC BY 4.0*.