VisNumBench: Evaluating Number Sense of Multimodal Large Language Models

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Abstract

Can Multimodal Large Language Models (MLLMs) develop an intuitive number sense similar to humans? Targeting this problem, we introduce Visual Number Benchmark (VisNumBench) to evaluate the number sense abilities of MLLMs across a wide range of visual numerical tasks. VisNumBench consists of about 1,900 multiplechoice question-answer pairs derived from both synthetic and real-world visual data, covering seven visual numerical attributes and four types of visual numerical estimation tasks. Our experiments on VisNumBench led to the following key findings: (i) The 17 MLLMs we tested—including open-source models such as Owen2.5-VL and InternVL2.5, as well as proprietary models like GPT-40 and Gemini 2.0 Flash—perform significantly below human levels in number sense-related tasks. (ii) Multimodal mathematical models and multimodal chain-of-thought (CoT) models did not exhibit significant improvements in number sense abilities. (iii) Stronger MLLMs with larger parameter sizes and broader general abilities demonstrate modest gains in number sense abilities. We believe VisNum-Bench will serve as a valuable resource for the research community, encouraging further advancements in enhancing MLLMs' number sense abilities. All benchmark resources, including code and datasets, will be publicly available at https://wwwtttjjj.github.io/VisNumBench/.

1. Introduction

Number sense is an innate cognitive ability shared by both humans and animals through the approximate number system [14]. It enables individuals to perceive, process, and manipulate numerical information intuitively. By fostering a deeper understanding of abstract number concepts, it facilitates the grasp of complex mathematical theories and their

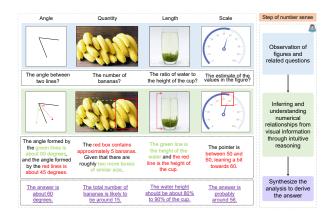


Figure 1: Explanations of number sense: how humans intuitively perceive and estimate values of angle, quantity, length, and scale.

practical application in real-world scenarios. Figure 1 illustrates the human ability to perceive and estimate numerical quantities. For instance, a person can quickly recognize a group of five bananas and intuitively estimate that there are about two more groups of the same size. By leveraging this innate number sense and grouping strategy, one can infer that the total number of bananas is approximately fifteen.

Multimodal Large Language Models (MLLMs) have made remarkable strides in tackling complex multimodal tasks [2, 7, 24, 26]. Recent research has focused on enhancing their mathematical and scientific reasoning capabilities by incorporating external tools [31, 49]. To assess these abilities, numerous benchmarks [30, 10, 32, 29, 20, 18] have been developed to evaluate the performance of MLLMs on mathematical reasoning and numerical interpretation tasks. While existing benchmarks effectively assess structured numerical reasoning problems, they primarily emphasize abstract symbolic computation, mathematical problemsolving, or interpreting numerical data in textual contexts.

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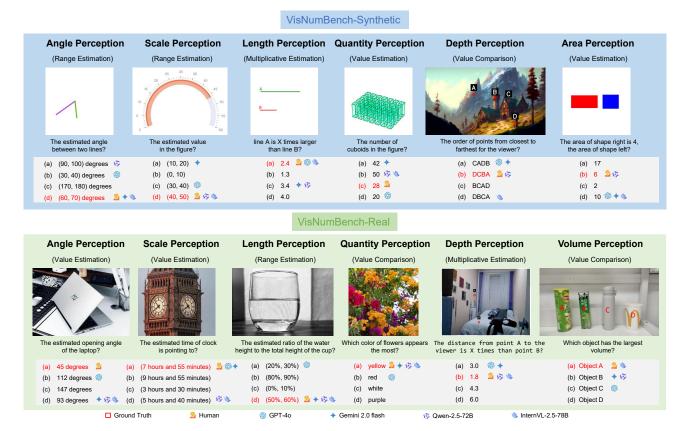


Figure 2: Examples from VisNumBench and responses from MLLMs. VisNumBench is divided into two subsets: VisNumBench-Synthetic and VisNumBench-Real. It focuses on seven key visual numerical attributes: angle, scale, length, quantity, depth, area, and volume. Even state-of-the-art MLLMs often struggle to answer the questions in VisNumBench accurately.

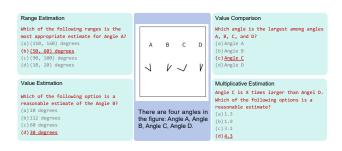


Figure 3: Illustrations of four distinct visual numerical estimation tasks: range estimation, value comparison, value estimation, and multiplicative estimation.

However, these evaluations overlook a critical aspect of human-like numerical cognition: intuitive number sense. Unlike humans, who effortlessly estimate quantities, perceive proportions, and grasp numerical relationships at a glance, MLLMs often depend on explicit reasoning steps rather than perceptual intuition. This limitation raises fundamental questions about whether current models genuinely comprehend numerical concepts or merely manipulate them

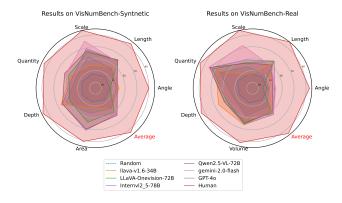


Figure 4: Evaluation results of MLLMs on the VisNum-Bench. The performance of MLLMs on VisNumBench is significantly poor in terms of accuracy, whereas human performance is nearly perfect.

based on learned patterns in text and images.

In this work, we introduce the Visual Number Benchmark (VisNumBench), inspired by human number sense

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VNS-Bench	Angle	Length	Scale	Quantity	Depth	Area	Volume	Total
VNS-Bench-Synthetic	170	181	140	196	135	189	-	1011
VNS-Bench-Real	149	162	143	147	154	-	147	902
Answer Format	4/5 options	3/4 options	4 options	3/4 options	4 options	4/5 options	3/4 options	3/4/5 options

abilities. As illustrated in Figure 2, VisNumBench is structured into two components based on different visual scenarios: VisNumBench-Synthetic and VisNumBench-Real. VisNumBench-Synthetic comprises controlled, synthetic images in which numerical relationships are explicitly defined. VisNumBench-Real contains real-world images, providing a more complex and less controlled environment. Grounded in human number sense, VisNumBench targets seven key dimensions of visual numerical attributes through four distinct types of visual numerical estimation tasks, as depicted in Figure 3.

We evaluated 17 MLLMs on VisNumBench and found that even state-of-the-art models perform poorly on our proposed benchmark, which is shown in Figure 4. Furthermore, our experiments reveal that adopting multimodal mathematical models and multimodal Chain-of-Thought (CoT) models did not lead to substantial performance improvements. However, the performance of the latest models is better than the previous models from the same family. For example, Qwen2.5VL [41] performs better than Qwen2VL [44]. It seems that optimization on data, training techniques, and model architecture will help models improve number sense ability. Within this work, we aim at advancing MLLMs toward higher levels of intelligence by developing models that enhance visual number sense abilities.

The main contributions of this paper are listed as follows:

- We introduce VisNumBench, a comprehensive benchmark that integrates diverse data sources and an automated evaluation framework to assess the numerical sense abilities of MLLMs across various visual numeric tasks.
- We conduct a comprehensive evaluation of various MLLMs on VisNumBench and find that even the most advanced models still demonstrate limited numerical sense abilities.
- 3. Further experiments on historical models from the same family show that their numerical sense abilities have improved over time. To enhance this ability within a short period, more specialized optimizations in data, training techniques, and model architecture may be required.

2. Related Work

2.1. Multimodal Large Language Models

Recent advancements in MLLMs have demonstrated exceptional capabilities across a wide range of tasks. Leveraging multimodal pre-training, MLLMs have achieved outstanding performance in both open-source models [51, 1, 45, 4, 5] and proprietary models [34, 36, 3]. Consequently, these models have been widely adopted in various domains, including mathematical reasoning [55], chart understanding [33], medical image analysis [23], and text-rich image comprehension [56]. Their growing success has spurred the development of an increasing number of benchmarks to assess performance across diverse visual and linguistic tasks.

2.2. Benchmarks for MLLMs

Advancements in MLLMs have led to the development of numerous benchmarks aimed at evaluating model performance across a broad spectrum of general multimodal tasks. Several recent studies [15, 53, 28, 22, 21, 52] have introduced more comprehensive multimodal benchmarks that provide extensive and holistic assessments. Beyond general multimodal tasks, specialized benchmarks have been created to evaluate the mathematical reasoning capabilities of MLLMs. Tasks such as visual reasoning with numbers, arithmetic problem-solving, and algebraic manipulation play a crucial role in assessing both the numerical proficiency and higher-order cognitive abilities of MLLMs. Prominent benchmarks, including MATH-VISTA [29], Math-Vision [43], MathOdyssey [13], and SMART-840 [9], are designed to test models on a diverse range of mathematical challenges, such as word problems, equation-solving, and complex multi-step reasoning.

These benchmarks aim to assess the ability of models to understand and process mathematical content in both images and text, as well as their ability to apply mathematical operations in reasoning contexts. However, evaluating MLLMs is crucial not only for measuring their proficiency in traditional mathematical reasoning but also for understanding their ability to handle more tangible, real-world dependent mathematical perception tasks. Humans typically acquire basic mathematical knowledge through intuitive number sense, which they then apply to real-world sce-

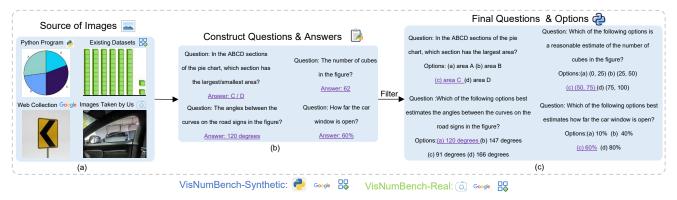


Figure 5: An illustration of the construction steps for images and questions in VisNumBench-Synthetic and VisNumBench-Real.

narios. This intuitive understanding of numbers and their relationships is a fundamental aspect of human cognition, enabling the seamless application of mathematical concepts in everyday life. While MLLMs can process complex mathematical problems, they may struggle with tasks that require this intuitive number sense. Therefore, existing benchmarks should not only evaluate the proficiency of models in traditional mathematical reasoning but also assess their ability to apply mathematical concepts in real-world contexts. This would help bridge the gap between abstract problem-solving and practical application.

2.3. Number Sense of MLLMs

In the context of MLLMs, previous research [25, 46, 11] has focused on tasks that rely on ordinal regression to evaluate number sense. Examples of such tasks include Age Estimation [37], Historical Image Dating [35], and Image Aesthetics Assessment [38]. These studies typically focus on estimating or ranking numerical attributes based on visual input, such as predicting the age of a person in an image or determining the historical context of a photograph. While these tasks assess the ability of the model to interpret numerical cues and sequences, they often focus on specific domains and may overlook the broader, more generalizable concept of number sense.

Assessing the number sense of MLLMs refers to evaluating their number sense abilities in a variety of scenarios. This includes tasks such as interpreting measurements, performing approximate calculations, comparing quantities, and identifying numerical relationships in different contexts. Such evaluations provide a better understanding of how models perform on tasks that require flexible and contextual reasoning about numbers while also enhancing their broad applicability and intelligence.

3. VisNumBench

3.1. Overview

We introduce VisNumBench, a benchmark specifically designed to directly evaluate the intuitive numerical abilities of MLLMs. Each instance in VisNumBench comprises a figure, a multiple-choice question, and a corresponding answer label. The dataset statistics of VisNumBench are presented in Table 1.

Compared with previous benchmarks, VisNumBench has the following novel features:

- Comprehensive Scenario Integration: VisNum-Bench incorporates both controlled synthetic figures and intricate real-world scenes, enabling a thorough evaluation of the number sense abilities of MLLMs.
- Multidimensional Visual Numerical Attributes:
 VisNumBench encompasses seven fundamental aspects of number sense—angle, length, scale, quantity, depth, area, and volume—ensuring a rigorous and comprehensive evaluation of the numerical capabilities of MLLMs.
- Comprehensive Visual Numerical Estimation Tasks: VisNumBench encompasses four distinct modes of visual numerical estimation—value comparison, value estimation, range estimation, and multiplicative estimation. These diverse tasks enable a thorough evaluation of MLLMs' ability to estimate numerical values across different visual numerical categories.

3.2. Data Collection Process

3.2.1 Source of Images

The development of VisNumBench required gathering figures from diverse sources, as depicted in part (a) of Figure 5.

Table 2: Accuracies of MLLMs on the VisNumBench-Synthetic (%) dataset.	Dark gray	and	light gray	indicate the best
and the second best results among all models, respectively.				

	A 1	T .1	G 1	0 .:.	D .1					
	Angle	Length	Scale	Quantity	Depth	Area	Average			
Random	24.44	25.41	25.00	25.00	25.00	23.68	24.76			
Open-source MLLMs										
Phi-3.5-vision	19.41	40.88	41.43	26.53	26.67	39.15	32.34			
LLaVA-v1.5-7B	31.18	30.39	34.29	33.16	26.67	21.16	29.38			
LLaVA-v1.5-13B	35.88	30.94	32.14	36.73	33.33	24.34	32.15			
LLaVA-v1.6-34B	40.00	45.30	40.00	46.94	64.44	33.33	44.31			
LLaVA-Onevision-7B	25.88	51.38	42.86	38.78	34.81	44.44	39.96			
LLaVA-Onevision-72B	24.71	61.33	62.14	50.00	48.15	58.73	50.84			
InternVL2.5-8B	26.47	41.99	49.29	34.69	41.48	46.03	39.66			
InternVL2.5-38B	39.41	59.67	59.29	54.08	60.74	61.38	55.59			
InternVL2.5-78B	35.29	59.67	68.57	42.86	61.48	72.49	56.18			
Janus-Pro-7B	31.76	43.65	45.71	35.71	33.33	36.51	37.69			
Qwen2.5-VL-3B	30.00	49.17	50.71	32.14	42.22	51.85	42.43			
Qwen2.5-VL-7B	23.53	53.59	55.00	39.29	48.89	58.20	46.19			
Qwen2.5-VL-72B	37.06	59.67	65.00	57.65	61.48	70.37	58.46			
		API-ba	ased mod	els						
GPT-40	35.29	43.09	54.29	37.24	54.07	43.39	43.72			
Gemini 1.5 Flash	26.47	47.41	44.40	26.02	23.70	41.27	33.33			
Gemini 2.0 Flash	31.18	57.46	81.43	55.10	51.11	70.90	57.57			
Gemini 1.5 Pro	34.12	39.23	47.14	40.82	58.52	48.15	44.02			
Human	90.00	96.00	100.00	96.00	98.00	92.00	95.33			

- **Python Program.** We developed a series of Python scripts based on Matplotlib¹ to generate figures by randomly sampling parameters, which are also stored for future use. This approach allows precise control over various numerical properties, ensuring a well-balanced data distribution and minimizing potential biases.
- Existing Datasets. To enhance the diversity of the proposed benchmark and leverage existing high-quality data, we incorporated figures from multiple well-established datasets [29, 20, 16, 57, 40, 48]. These datasets encompassed a broad range of numerical and spatial reasoning scenarios.
- Web Collection. To incorporate more natural and diverse visual data, we gathered figures containing numerical information from publicly available web resources [42, 17, 12]. These figures were carefully curated and filtered to ensure relevance and clarity before designing the corresponding questions.
- Images Taken by Us. To better reflect real-world conditions, we manually constructed various number

sense scenarios and captured images using a camera. These scenes encompassed real-world measurements, physical counting tasks, and estimation challenges under natural lighting and occlusion conditions.

3.2.2 Construction of QA Pairs and Data Quality Control

As shown in parts (b) and (c) in Figure 5, we involve QA pairs for images from different sources. For the figures generated by the Python program, we manually design different questions based on the specific characteristics of each figure and generate corresponding annotations using the parameters saved We can design the question such as: "In the ABCD sections of the pie chart, which section has the largest/smallest area?" Based on the parameters saved, the answer would be "C/D". For images from other sources, we manually designed questions and annotated them based on different numerical attributes of the images. In addition, we can generate different numerical estimation tasks based on the answer type. For example, for the question: "Which of the following options is a reasonable estimate of the number of cubes in the figure?", when the answer is "(50, 75)", it corresponds to a range estimation task. On the contrary, if

¹https://matplotlib.org/

Table 3: Accuracies of MLLMs on the VisNumBench-Real (%) dataset. Dark gray and Light gray indicate the best and second-best results among all models, respectively.

	Angle	Length	Scale	Quantity	Depth	Volume	Average		
Random	25.00	25.00	25.00	27.83	25.00	25.40	25.54		
	Open-source MLLMs								
Phi-3.5-vision	30.20	37.65	27.97	48.30	48.70	29.93	37.25		
LLaVA-v1.5-7B	22.82	32.72	25.87	36.73	25.32	27.21	28.49		
LLaVA-v1.5-13B	28.86	43.21	29.37	46.94	49.35	41.50	40.02		
LLaVA-v1.6-34B	28.86	54.94	23.08	68.03	63.64	63.27	50.55		
LLaVA-Onevision-7B	18.12	44.44	20.28	64.63	44.81	50.34	40.58		
LLaVA-Onevision-72B	17.45	57.41	44.76	74.83	48.70	61.22	50.78		
InternVL2.5-8B	28.86	34.57	15.38	64.63	49.35	47.62	40.13		
InternVL2.5-38B	30.20	51.85	26.57	83.67	61.04	58.50	52.11		
InternVL2.5-78B	36.91	58.64	48.95	79.59	52.60	62.59	56.54		
Janus-Pro-7B	22.82	32.10	35.66	48.98	35.71	30.61	34.26		
Qwen2.5-VL-3B	30.20	44.44	35.66	51.70	43.51	49.66	42.57		
Qwen2.5-VL-7B	24.16	38.89	32.17	59.18	48.70	42.86	41.02		
Qwen2.5-VL-72B	34.23	50.62	43.36	80.27	52.60	59.18	53.33		
		API-b	ased mod	lels					
GPT-40	27.52	30.25	37.06	60.54	35.71	47.62	39.58		
Gemini 1.5 Flash	14.77	35.80	26.57	57.14	24.68	43.54	33.70		
Gemini 2.0 Flash	38.93	48.77	74.14	81.63	46.10	51.70	56.54		
Gemini 1.5 Pro	30.20	45.68	27.97	68.03	64.29	55.10	48.67		
Human	96.00	100.00	100.00	98.00	96.00	94.00	97.33		

the answer is "62", it belongs to the value estimation task.

We employ a combination of automated and manual methods to design distractors. For numerical answers, we generate alternative options that are easily confusable with the correct answer. Some distractors are constructed based on their inherent properties (e.g., areas A, B, and D in part (c) of Figure 5). These distractors are selected to align with human perceptual biases, ensuring that they appear plausible while remaining distinguishable from the correct answer.

To ensure the high quality of VisNumBench, we meticulously reviewed all collected data and filtered out any ambiguous or unclear entries. More details of the data construction process can be found in Appendix B.

4. Experiments

We evaluate 17 well-known MLLMs from 8 model families, including 13 open-source models: Phi-3.5-vision [1], LLaVA-v1.5 (7B, 13B), and LLaVA-v1.6-34B [27], LLaVA-Onevision (7B, 72B) [23], Qwen2.5-VL (3B, 7B, 72B) [41], InternVL2.5 (8B, 38B, 78B) [5], and Janus-Pro-7B [4]. Additionally, we assess 4 proprietary models: GPT-40 [19], Gemini 1.5 Flash, Gemini 2.0 Flash,

and Gemini 1.5 Pro [36].

We randomly selected 600 samples (50 QA pairs from each category), with 300 sourced from VisNumBench-Synthetic and 300 from VisNumBench-Real. Human evaluators independently answered each question and provided assessments. Accuracy (%) is reported for all experimental results, and all the results are provided in Tables 2 and 3.

4.1. Evaluation Results and Analysis

From Tables 2 and 3, we observe that the performance of MLLMs is not comparable to that of humans. Among the seven types of questions, quantity-related tasks appear to be the easiest, while angle-related tasks are the most difficult. This is possibly because the amount of data available for quantity-related tasks is significantly greater than that for angle-related tasks. By comparing the evaluations on synthetic and real images, we find that the performance of the same model does not exhibit significant variance. Thus, in terms of numerical reasoning ability, both synthetic and real images present similar challenges for existing MLLMs. Moreover, we observe that the best opensourced model performs comparably to the best closed-source models. More detailed analyses and discussions are

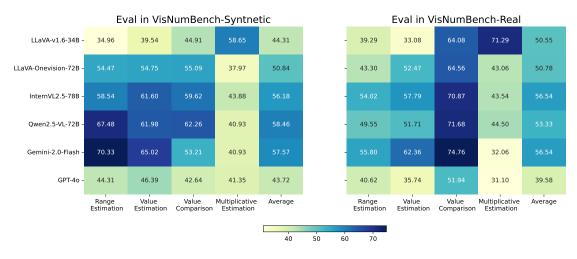


Figure 6: Confusion matrices of MLLMs of VisNumBench-Synthetic and VisNumBench-Real for different visual numerical estimation tasks.

provided in the following subsections.

4.1.1 Performance on VisNumBench-Synthetic

Table 2 presents the results for various MLLMs on the VisNumBench-Synthetic dataset. Among the open-source models, Qwen2.5-VL-72B achieves the best performance, with an average accuracy of 58.46%. InternVL2.5-38B, InternVL2.5-78B, and LLaVA-v1.6-34B also demonstrate strong performance, each achieving either the best or the second-best accuracy in at least two tasks. LLaVA-v1.6-34B attains the highest accuracy in angle and depth estimation; however, its overall average accuracy is only 44.31%. LLaVA-Onevision-72B also performs well, achieving the highest accuracy in length estimation at 61.33%. In general, models with larger parameter sizes tend to exhibit superior performance, aligning with the intuition that larger models can better capture complex numerical relationships and fine-grained visual patterns.

In the API-based models, Gemini 2.0 Flash demonstrates the best performance, achieving an average accuracy of 57.57%. In contrast, GPT-40 and Gemini 1.5 Pro exhibit comparable performance, albeit with lower average accuracies. Gemini 1.5 Flash yields the weakest performance, with an average accuracy of 33.33%. Notably, certain open-source models perform on par with or even surpass proprietary models, suggesting that the disparity in numerical reasoning capabilities between open-source and closed-source models is minimal.

4.1.2 Performance on VisNumBench-Real

Accuracy on the VisNumBench-Real dataset shows similar trends. InternVL2.5-78B and Gemini 2.0 Flash stand out with an average accuracy of 56.54%, achieving near-optimal results across multiple tasks, as shown in Table 3.

InternVL2.5-38B attained an exceptionally high accuracy of 83.67% on the quantity task, while LLaVA-v1.6-34B excelled in the volume task, achieving the highest scores. Qwen2.5-VL-72B demonstrated relatively balanced performance across tasks, yielding a suboptimal average accuracy of 53.33%.

Surprisingly, Gemini 1.5 Pro achieved the highest accuracy in depth estimation, reaching 64.29%. However, its overall average accuracy remained unsatisfactory. Other proprietary models, such as GPT-40 and Gemini 1.5 Flash, exhibited relatively weaker performance. In general, the accuracy on VisNumBench-Real is lower than that on VisNumBench-Synthetic, likely due to the increased complexity and variability of real-world images.

4.1.3 Performance on Different Visual Numerical Estimation Tasks

As we analyze performance across different numerical estimation tasks, Figure 6 reveals that in the synthetic scenario, Gemini 2.0 Flash and Qwen2.5-VL-72B achieve the highest performance across all sub-tasks, particularly in range estimation, value estimation, and value comparison, where their scores consistently exceed 60. In contrast, GPT-40 exhibits the lowest performance in all tasks, especially in value comparison and multiplicative estimation. In the realworld scenario, most models achieved their best performance in value comparison tasks, which are also the easiest for humans. Although Gemini 2.0 Flash and InternVL2.5-78B continue to perform well in most tasks, their performance in multiplicative estimation has declined compared to the synthetic scenario. Additionally, GPT-40 continues to perform poorly across all tasks, particularly in multiplicative estimation and value comparison, where it falls significantly behind other models.

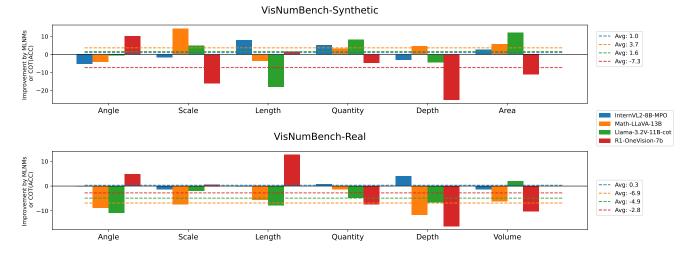


Figure 7: Improvements brought by multimodal mathematical models (InternVL2-8B-MPO and Math-LLaVA-13B) and multimodal CoT models (Llama-3.2V-11B-cot and R1-OneVision-7B). Table 8 and Table 9 in the appendix provides detail results.

Notably, in the multiplicative estimation task, LLaVA-v1.6-34B outperforms all other models by a significant margin. This suggests that certain models may be more specialized for specific types of tasks, and further fine-tuning or adjustments could enhance performance across different tasks.

4.2. Further Analysis

How do math-special models perform on the Vis-NumBench? To investigate the number sense abilities of math-special models, we introduce two multimodal mathematical models: (1) InternVL2-8B-MPO [47], initialized from InternVL2-8B [8] and fine-tuned on the largescale multimodal reasoning preference dataset MMPR [47], achieving the score of 65.65 on MathVista; (2) Math-LLaVA-13B [39], initialized from LLaVA-v1.5-13B and fine-tuned on the MathV360K [39] dataset. As shown in Figure 7, InternVL2-8B-MPO achieved a 1.0% improvement in synthetic scenarios and a 0.3% increase in realworld scenarios. Its enhancements are task-specific rather than universally effective across different number sense challenges. In contrast, Math-LLaVA-13B exhibited a polarized performance trend: while it improved by 3.7% on the synthetic dataset, its accuracy declined by 6.9% in realworld scenarios. This suggests that although the model benefits from training on synthetic data, it struggles to generalize to the complexity and variability of real-world number sense tasks. Relying solely on synthetic data may be insufficient to enhance number sense capabilities in real-world applications. Additional strategies, such as incorporating more diverse real-world training data or refining model architectures, may be necessary to achieve meaningful im-

Table 4: Comparisons of the performance of models from the Qwen-VL family and the InternVL family in synthetic and real-world scenes. Table 10 in the appendix provides further detailed results.

	Average (Synthetic)	Average (Real)
Qwen2-VL-2B	31.85	24.94
Qwen2.5-VL-3B	$42.24(\uparrow +10.39)$	$42.57(\uparrow +17.63)$
Qwen2-VL-7B	41.25	41.91
Qwen2.5-VL-7B	$46.19(\uparrow +4.94)$	$41.02(\downarrow -0.89)$
Qwen2-VL-72B	54.20	46.56
Qwen2.5-VL-72B	$58.46(\uparrow +4.26)$	$53.33(\uparrow +6.77)$
InternVL2-8B	39.56	39.58
InternVL2.5-8B	$39.66(\uparrow +0.10)$	$40.13(\uparrow +0.55)$
InternVL2-40B	45.50	45.12
InternVL2.5-38B	$55.59(\uparrow +10.09)$	$52.11(\uparrow +6.99)$

provements.

How do the multimodal reasoning models perform? To examine whether reasoning techniques can enhance the number sense abilities of MLLMs, we evaluate two multimodal reasoning models: Llama-3.2V-11B-cot² [50] and R1-OneVision-7B³. Llama-3.2V-11B-cot is trained using LLaVA-o1-100k [50], achieving a 6.2% performance improvement on MathVista compared to Llama-3.2-11B-

³https://github.com/Fancy-MLLM/R1-Onevision

Vision-Instruct. R1-OneVision-7B, trained with a rule
2https://huggingface.co/Xkev/Llama-3.2V-11B-cot

based reinforcement learning technique, attains an accuracy of 44.06% on Mathverse [54]. Accordingly, we assess these models on our benchmark. The results, presented in Figure 7, indicate that neither Llama-3.2V-11B-cot nor R1-OneVision-7B achieved the expected performance gains. On the contrary, their accuracy dropped significantly—except for a modest 1.6% improvement by Llama-3.2V-11B-cot in synthetic scenarios—especially in real-world settings. These findings suggest that developing reasoning techniques specifically tailored for number sense abilities may be necessary.

What helps improve the performance? To determine the factors contributing to the improvement of number sense ability in MLLMs, we evaluate historical models from the same family over time, specifically the Qwen-VL family and the InternVL family. The results are presented in Table 4. As observed, the performance of the latest models generally surpasses that of their predecessors. By comparing Qwen2-VL [44] with Qwen2.5-VL [41], as well as InternVL2 with InternVL2.5 [6], we observe improvements in several aspects: (1) data scale and quality, (2) a more powerful encoder, (3) model architecture, and (4) training strategy. These findings suggest that further exploration in these directions is essential for enhancing the number sense abilities of MLLMs.

5. Conclusion

In this work, we introduce VisNumBench, a novel benchmark designed to evaluate MLLMs on core number sense abilities that are inadequately addressed by existing evaluation benchmarks. Our assessment of 17 MLLMs uncovers substantial deficiencies in their capacity to demonstrate human-like number sense. Even the most advanced models still demonstrate limited numerical sense abilities. Further experiments on historical models from the same family show that to enhance this ability within a short period, more specialized optimizations in data, training techniques, and model architecture may be required.

6. Acknowledge

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A. Appendix Outline

In the supplementary materials, we present:

- A detailed explanation of the VisNumBench construction process (Appendix B);
- The evaluation setup and comprehensive results for VisNumBench sub-experiments (Appendix C);
- Additional visualizations (Appendix D).

B. Details for VisNumBench Construction

Angle The task may involve recognizing angles in both 2D and 3D contexts, such as the angles between intersecting lines or the angle between the viewpoint and an object. The figures for VisNumBench-Synthetic are either generated using Python programs or sourced from VisOnlyQA [20], whereas the images for VisNumBench-Real are either captured by the authors or collected from Google Images [17]. Length Based on synthetic and real scenes, we designed various types of question-answering questions, such as relative length comparison and multiple estimation of line segments, as well as the estimation of length, height, and proportion of different objects, among others. The figures for VisNumBench-Synthetic are either generated by Python programs or sourced from MathVista [29], whereas the figures for VisNumBench-Real are captured by the authors or collected from Google Images [17].

Scale We provide figures illustrating the coordinates of a point in a coordinate system, the time indicated on a clock, and the temperature displayed on a thermometer. The figures for VisNumBench-Synthetic are generated by Python programs, sourced from MathVista [20], while other figures originate from Google Images [17] and ECharts [12]. In contrast, the statistics for VisNumBench-Real are either captured by the authors or collected from Google Images [17].

Quantity Each figure contains a varying number of objects, such as points or triangles in synthetic scenarios, or hot air balloons or pets in real-world scenarios. The figures for VisNumBench-Synthetic are either generated using Python programs or obtained from MathVista [29], whereas the figures for VisNumBench-Real are sourced from Google Images [17] and the ShanghaiTech dataset [57].

Depth We further refine the "Relative Depth" task in BLINK [16] by incorporating additional choice points and introducing new question-answer formats. MLLMs will be presented with images containing objects at varying depths, requiring them to determine the correct depth order or estimate the relative distances between objects.

The figures for VisNumBench-Synthetic are obtained from the WallpapersCraft website [42] or sourced from MathVista [29] and VSLAM-TartanAir [48]. The figures

for VisNumBench-Real are sourced from BLINK [16] and the NYU Depth Dataset V2 [40].

Area VisNumBench-Synthetic contains comparisons and estimations of object area sizes for both identical and different shapes, as well as their multiplicative relationships. The figures in VisNumBench-Synthetic are either generated by Python programs or obtained from VisOnlyQA [20].

Volume Objects are presented from different perspectives and in various sizes, requiring MLLMs to infer relative volume sizes and proportions based on visible dimensions and depth. The figures for VisNumBench-Real are obtained through camera capture or sourced from Google Images [17].

More details of data construction are shown in the Tables 5, 6. Figure 8 shows the dataset statistics of VisNum-Bench based on various visual numerical estimation tasks. Figure 9 shows how to build a QA pair based on images generated by a Python script.

Table 5: The source distribution of different visual numerical attributes on the VisNumBench-Synthetic set.

	Python Program	Web Collection	Other Dataset	Total
Angle	138	0	32	170
Length	160	0	21	181
Scale	77	50	13	140
Quantity	185	0	11	196
Depth	0	70	65	135
Area	139	0	50	189
Total	699	120	192	1011

Table 6: The source distribution of different visual numerical attributes on the VisNumBench-Real set.

	Image Taken by Us	Web Collection	Other Dataset	Total
Angle	91	58	0	149
Length	144	18	0	162
Scale	21	122	0	143
Quantity	0	113	34	147
Depth	0	0	154	154
Volume	140	7	0	147
Total	396	318	188	902

C. Evalution Details

C.1. Model Access

This section details the model access and model parameters (refer to Table 7). The model responses presented in this paper were collected between January 1 and February 28, 2025.

C.2. Additional Results

This section provides additional results of experiments in Section 4.2.

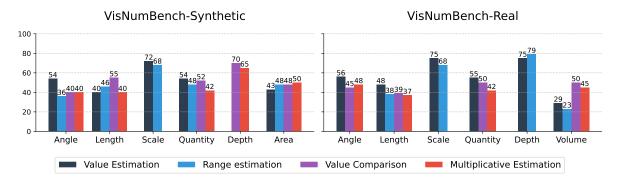


Figure 8: Dataset statistics of VisNumBench based on various visual numerical estimation tasks.

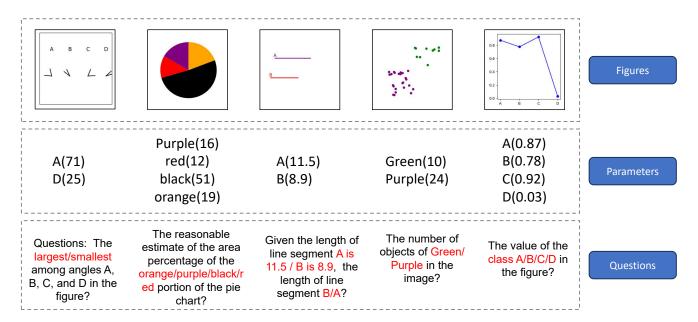


Figure 9: Example of the data generated by Python and manually designed questions.

Tablse 8 and 9 show the results by multimodal mathematical models and multimodal CoT models, corresponding to Figure 7. Table 10 presents the performance of models of varying sizes from the QwenVL and InternVL families, extending the results reported in Table 4.

C.3. Error Analysis

We take the results of Gemini 2.0 Flash as an example to conduct an error analysis. Based on these results, we randomly selected 10 erroneous instances for each attribute in each scenario and manually analyzed a total of 120 randomly sampled errors across all tasks. We categorize the errors into two types: (1) Errors resulting from the model's failure to correctly perceive the image (image perception errors). (2) Errors where the model correctly interprets the image and the question but fails to generate the correct numerical answer (numerical intuition errors). Our

findings indicate that 28.3% of the errors stem from image perception errors, particularly in scale-related tasks, where the model struggles to recognize the position of pointers. In 71.7% of cases, the model exhibits numerical intuition errors, which manifest in challenges related to depth estimation, angle relationships, and quantity perception. These findings further confirm that the current model indeed lacks robust numerical intuition.

Table 7: The MLLMs evaluated in this paper. This table presents the model names (Hugging Face repository name or Official API name).

Phi-3.5-vision	microsoft/Phi-3.5-vision-instruct
LLaVA-v1.5-7B	liuhaotian/llava-v1.5-7b
LLaVA-v1.5-13B	liuhaotian/llava-v1.5-13b
LLaVA-v1.6-34B	liuhaotian/llava-v1.6-34b
LLaVA-Onevision-7B	llava-hf/llava-onevision-qwen2-72b-si-hf
LLaVA-Onevision-72B	llava-hf/llava-onevision-qwen2-72b-ov-hf
InternVL2.5-8B	OpenGVLab/InternVL2_5-8B
InternVL2.5-38B	OpenGVLab/InternVL2_5-38B
InternVL2.5-78B	OpenGVLab/InternVL2_5-78B
Janus-Pro-7B	deepseek-ai/Janus-Pro-7B
Qwen2.5-VL-3B	Qwen/Qwen2.5-VL-3B-Instruct
Qwen2.5-VL-7B	Qwen/Qwen2.5-VL-7B-Instruct
Qwen2.5-VL-72B	Qwen/Qwen2.5-VL-72B-Instruct
GPT-40	gpt-4o-2024-08-06
Gemini 1.5 Flash	gemini-1.5-flash
Gemini 2.0 Flash	gemini-2.0-flash
Gemini 1.5 Pro	gemini-1.5-pro-002

D. Example Data and Model Outputs

Figures 10 to 21 show examples from VisNumBench and the responses of Gemini 2.0 Flash.

Table 8: Accuracies of multimodal mathematical models, multimodal CoT models, and their respective base models (before fine-tuning) on VisNumBench-Synthetic.

Models	Angle	Length	Scale	Quantity	Depth	Area	Average			
multimodal mathematical models										
Internvl-8B	28.24	49.72	55.00	28.57	31.11	46.03	39.56			
InternVL2-8B-MPO	22.94	48.07	63.57	33.67	28.15	48.68	40.65			
LLaVA-v1.5-13B	35.88	30.94	32.14	36.73	33.33	24.34	32.15			
Math-LLaVA-13B	31.76	45.30	28.57	39.80	37.78	30.16	35.81			
	m	ultimodal	CoT mo	odels						
Llama-VL-3_2-11B	29.41	41.44	58.57	47.96	42.96	44.97	43.92			
Llama-3.2V-11B-cot	28.82	46.41	40.71	56.12	38.52	57.14	45.50			
Qwen2.5-VL-7B-Instruct	23.53	53.59	55.00	39.29	48.89	58.20	46.19			
R1-Onevision-7B	33.53	37.57	56.43	34.69	23.70	47.09	38.87			

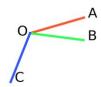
Table 9: Accuracies of multimodal mathematical models, multimodal CoT models, and their respective base models (before fine-tuning) on VisNumBench-Real.

	Angle	Length	Scale	Quantity	Depth	Area	Average				
multimodal mathematical models											
Internvl-8B	30.87	36.42	29.37	71.43	30.52	39.46	39.58				
InternVL2-8B-MPO	30.87	35.19	29.37	72.11	34.42	38.10	39.91				
LLaVA-v1.5-13B	28.86	43.21	29.37	46.94	49.35	41.50	40.02				
Math-LLaVA-13B	20.13	35.80	23.78	45.58	37.66	35.37	33.15				
	m	ultimodal	CoT mo	odels							
Llama-VL-3_2-11B	38.26	40.74	30.77	69.39	38.31	42.18	43.24				
Llama-3.2V-11B-cot	27.52	38.89	23.08	64.63	31.82	44.22	38.36				
Qwen2.5-VL-7B-Instruct	24.16	38.89	32.17	59.18	48.70	42.86	41.02				
R1-Onevision-7B	28.86	39.51	44.76	51.70	32.47	32.65	38.25				

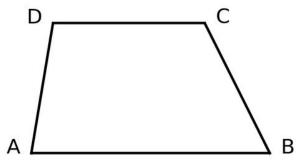
Table 10: Results of models with varying sizes from the QwenVL family and InternVL family on VisNumBench.

	Angle	Length	Scale	Quantity	Depth	Area/Volume	Average				
	VisNumBench-Systentic										
Qwen2-VL-2B	28.24	30.39	35.00	35.20	21.48	38.10	31.85				
Qwen2-VL-7B	27.06	45.30	55.00	44.39	34.81	46.56	42.24				
Qwen2-VL-72B	32.94	57.46	63.57	54.59	58.52	59.79	54.20				
Internvl-8B	28.24	49.72	55.00	28.57	31.11	46.03	39.56				
Internvl-40B	23.53	58.56	57.14	37.24	37.78	58.20	45.50				
Qwen2.5-VL-3B	30.00	49.17	50.71	32.14	42.22	51.85	42.43				
Qwen2.5-VL-7B	23.53	53.59	55.00	39.29	48.89	58.20	46.19				
Qwen2.5-VL-72B	37.06	59.67	65.00	57.65	61.48	70.37	58.46				
InternVL2.5-8B	26.47	41.99	49.29	34.69	41.48	46.03	39.66				
InternVL2.5-38B	39.41	59.67	59.29	54.08	60.74	61.38	55.59				
		Vi	sNumB	ench-Real							
Qwen2-VL-2B	10.74	19.75	19.58	47.62	32.47	19.73	24.94				
Qwen2-VL-7B	19.46	38.89	30.07	67.35	41.56	54.42	41.91				
Qwen2-VL-72B	21.48	45.06	37.06	74.83	48.70	52.38	46.56				
Internvl-8B	30.87	36.42	29.37	71.43	30.52	39.46	39.58				
Internvl-40B	30.87	50.00	28.67	72.79	35.71	52.38	45.12				
Qwen2.5-VL-3B	30.20	44.44	35.66	51.70	43.51	49.66	42.57				
Qwen2.5-VL-7B	24.16	38.89	32.17	59.18	48.70	42.86	41.02				
Qwen2.5-VL-72B	34.23	50.62	43.36	80.27	52.60	59.18	53.33				
InternVL2.5-8B	28.86	34.57	15.38	64.63	49.35	47.62	40.13				
InternVL2.5-38B	30.20	51.85	26.57	83.67	61.04	58.50	52.11				

Synthetic (Angle)



Synthetic (Angle)



Prompt:

Question: Angle AOC is X times larger than Angel AOB. Which of the following options is a reasonable estimate for X?

Options: (a) 1.5 (b) 5.6 (c) 3.1 (d) 4.0

Please think and answer the question based on the most likely options.

Type: Multiplicative Estimation

Answer:(b) 5.6

Gemini 2.0 Flash:

Based on the image, angle AOC appears to be significantly larger than angle AOB. If angle AOC were about 3 times larger than angle AOB, then 3.1 (c) would be a reasonable estimate for X. 4.0 (d) would also be a reasonable estimate. Therefore, considering the options, and the size of AOB and AOC, the most reasonable estimate for x would be 4.0. So the answer is (d).

Prompt:

Question: Which angle is the largest among angles A, B, C, and D in the figure?

Options:(a) angle A (b) angle B (c) angle C (d) angle D

Please think and answer the question based on the most likely options.

Type: Value Comparison

Answer: (c) angle C

Gemini 2.0 Flash:

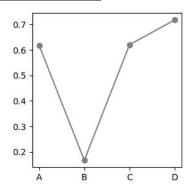
Based on the figure, angle B appears to be the largest angle. So the answer is (b).





Figure 10: Examples of VisNumBench and the results predicted by Gemini2.0 Flash (VisNumBench-Synthetic, Angle, 1/12).

Synthetic (Scale)



Prompt:

Question: Which of the following ranges is most likely to be the value of the class A in the figure? Options: (a) (0.20, 0.30) (b) (0.60, 0.70) (c) (0.40, 0.50) (d) (0.10, 0.20)

Please think and answer the question based on the most likely options.

Type: Range Estimation

Answer:(b) (0.60, 0.70)

Gemini 2.0 Flash:

Based on the image, the value of class A appears to be approximately 0.62. Therefore, none of the options are correct.

Synthetic (Scale)



Prompt:

Question: Which of the following options is a reasonable estimate of the time the clock in the figure is pointing to?

Options:(a) 12 hours and 37 minutes (b) 10 hours and 07 minutes (c) 3 hours and 00 minutes (d) 7 hours and 22 minutes

Please think and answer the question based on the most likely options.

Type: Value Estimation

Answer:(c) 3 hours and 00 minutes

Gemini 2.0 Flash:

Based on the image, the hour hand is pointing close to the 12, and the minute hand is pointing to around the number 7. Therefore, the reasonable estimate is **(a) 12 hours and 37 minutes**.





Figure 11: Examples of VisNumBench and the results predicted by Gemini2.0 Flash (VisNumBench-Synthetic, Scale, 2/12).

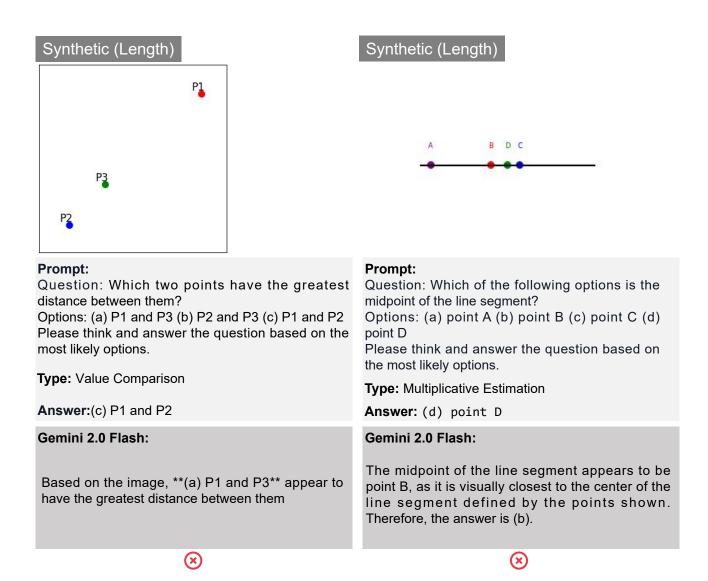
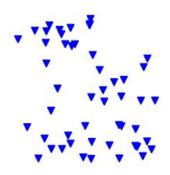


Figure 12: Examples of VisNumBench and the results predicted by Gemini2.0 Flash (VisNumBench-Synthetic, Length, 3/12).

Synthetic (Quantity)



Prompt:

Question: Which is a reasonable range of estimates for the number of blue objects in the figure?

Options: (a) [1, 10) (b) [10, 20) (c) [20, 30) (d) More

than 30

Please think and answer the question based on the most likely options.

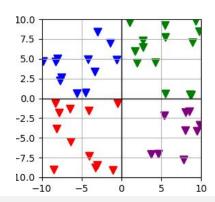
Type: Range Estimation

Answer:(d) More than 30

Gemini 2.0 Flash:

Based on the figure, there are more than 30 blue objects. So the answer is (d).

Synthetic (Quantity)



Prompt:

Question: Which of the following colors of objects in the figure is most likely to have the highest quantity? Options:(a) blue (b) green (c) purple (d) red Please think and answer the question based on the most likely options.

Type: Value Comparison

Answer: (b) green

Gemini 2.0 Flash:

Based on the figure, the color with the highest quantity of objects is **blue**. Therefore, the answer is (a).





Figure 13: Examples of VisNumBench and the results predicted by Gemini2.0 Flash (VisNumBench-Synthetic, Quantity, 4/12).

Synthetic (Depth)



Prompt:

Question: The depth from point B to the viewer is X times than point A, Which of the following options is a reasonable estimate?

Options: (a) 2.3 (b) 1.0 (c) 3.6 (d) 5.7

Please think and answer the question based on the most likely options.

Type: Multiplicative Estimation

Answer:(b) 1.0

Gemini 2.0 Flash:

The depth from point B to the viewer is greater than point A. By observation, the reasonable option is (a) 2.3.

Synthetic (Depth)



Prompt:

Question: Four points are circled on the figure, labeled by A, B, C and D beside each circle. Which point appears closer to the viewer?

Options:(a) A is closer (b) B is closer (c) C is closer (d) D is closer

Please think and answer the question based on the most likely options.

Type: Value Comparison **Answer**: (a) A is closer

Gemini 2.0 Flash:

The point C is part of the character, who appears to be in the foreground compared to the background with A, B, and D. So, the point C is closer. Therefore, the answer is (c)





Figure 14: Examples of VisNumBench and the results predicted by Gemini2.0 Flash (VisNumBench-Synthetic, Depth, 5/12).

Synthetic (Area)

Prompt:

Question: Which of the following options is a reasonable estimate of the area percentage of the red portion of the pie chart?

Options: (a) (70%, 80%) (b) (80%, 90%) (c) (20%, 30%) (d) (40%, 50%)

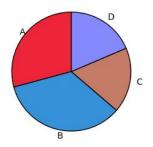
Please think and answer the question based on the

most likely options. **Type:** Range Estimation **Answer:**(c) (20%, 30%)

Gemini 2.0 Flash:

Based on the image, the red portion of the pie chart appears to be approximately one-fourth of the whole pie. One-fourth is equal to 25%. Therefore, the option that best represents this is (c) (20%, 30%).

Synthetic (Area)



Prompt:

Question: In the ABCD sections of the pie chart below, which section has the largest area? Options: (a) area A (b) area B (c) area C (d) area D Please think and answer the question based on the most likely options.

Type: Value Comparison

Answer: (b) area B

Gemini 2.0 Flash:

Based on the pie chart provided, area A appears to be the largest section. So the answer is (a) area A.





Figure 15: Examples of VisNumBench and the results predicted by Gemini2.0 Flash (VisNumBench-Synthetic, Area, 6/12).

Real (Angle)



Prompt:

Question: Which of the following options best estimates the angles between the branches in the figure?

Options: (a) (90, 100) degrees (b) (70, 80) degrees (c) (30, 40) degrees (d) (130, 140) degrees

Please think and answer the question based on the

most likely options.

Type: Range Estimation

Answer: (c) (30, 40) degrees

Gemini 2.0 Flash:

Based on the image, the angles between the branches are quite wide. Option (d), (130, 140) degrees, seems to best estimate the angles.

Real (Angle)



Prompt:

Question: The angle formed by the objects on the left side is X times the angle formed by the objects on the right side of the figure. Which of the following options is a reasonable estimate for X?

Options:(a) 1.0 (b) 3.3 (c) 2.0 (d) 4.2

Please think and answer the question based on the most likely options.

Type: Multiplicative Estimation

Answer: (c) 2.0

Gemini 2.0 Flash:

Let's analyze the angles formed by the objects on the left and right sides of the image. On the left, the angle between the two tubes is approximately 60 degrees. On the right, the angle between the two mice is approximately 20 degrees. To find the value of X, we divide the angle on the left by the angle on the right: X = 60 degrees / 20 degrees = 3Therefore, the angle formed by the objects on the left side is approximately 3 times the angle formed by the objects on the right side. Based on the options provided: (a) 1.0(b) 3.3(c) 2.0(d) 4.2The most reasonable estimate for X is 3.3. Final Answer: The final answer is \$\boxed{3.3}\$





Figure 16: Examples of VisNumBench and the results predicted by Gemini2.0 Flash (VisNumBench-Real, Angle, 7/12).

Real (Scale)



Prompt:

Question: Which of the following options is an reasonable estimate of the temperature in degrees Celsius that the thermometer in the figure is pointing to?

Options: (a) 36.4 (b) 37.1 (c) 38.0 (d) 39.4

Please think and answer the question based on the most likely options.

Type: Value Estimation
Answer: (a) 36.4

Gemini 2.0 Flash:

Based on the image, the thermometer reading appears to be slightly above 37 degrees Celsius. Therefore, the most reasonable estimate from the options is (b) 37.1.

Real (Scale)



Prompt:

Question: Which of the following options is an reasonable estimate of the value that the pointer in the figure is pointing to, regardless of whether it is positive or negative?

Options:(a) 8 (b) 1 (c) 10 (d) 3

Please think and answer the question based on the most likely options.

Type: Value Estimation

Answer: (c) 10

Gemini 2.0 Flash:

The pointer is pointing very close to the 1.0 mark. The question asks for a "reasonable estimate of the value that the pointer... is pointing to". Of the provided options, the value closest to 1 is (b) 1. Therefore, the answer is (b).





Figure 17: Examples of VisNumBench and the results predicted by Gemini2.0 Flash (VisNumBench-Real, Scale, 8/12).

Real (Length)



Prompt:

Question: The right object is X times higher than left object. Which of the following options is a

reasonable estimate for X?

Options: (a) 2.8 (b) 1.5 (c) 3.7 (d) 4.7

Please think and answer the question based on the

most likely options.

Type: Multiplicative Estimation

Answer: (b) 1.5

Gemini 2.0 Flash:

Based on visual estimation, the right object (spray bottle) appears to be roughly 2.5 to 3 times higher than the left object (electric razor). Therefore, option (a) 2.8 is the most reasonable estimate.

Real (Length)



Prompt:

Question: The objects from left to right in the figure are object A, object B, object C, and object D. Which object has the largest length?

Options:(a) object A (b) object B (c) object C (d) object D

Please think and answer the question based on the most likely options.

Type: Value Comparison

Answer: (a) object A

Gemini 2.0 Flash:

Based on the image, object A appears to have the largest length. The answer is (a).





Figure 18: Examples of VisNumBench and the results predicted by Gemini2.0 Flash (VisNumBench-Real, Length, 9/12).

Real (Quantity)



Prompt:

Question: Which of the following options is a reasonable estimate of pencil in the figure?

Options: (a) 70 (b) 26 (c) 43 (d) 54

Please think and answer the question based on the most likely options.

Type: Value Estimation

Answer:(c) 43

Gemini 2.0 Flash:

Based on the image, a reasonable estimate of the number of pencils is 54. So the answer is (d)

Real (Quantity)



Prompt:

Question: Which of the following options is a reasonable range of estimates for the number of bikes in the figure?

Options:(a) [1, 10) (b) [10, 30) (c) More than 30 Please think and answer the question based on the most likely options.

Type: Range Estimation **Answer:** (b) [10, 30)

Gemini 2.0 Flash:

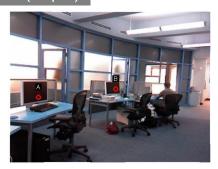
Based on the image, there are clearly more than 10 bikes visible. Counting them suggests there are more than 30 bikes. Therefore, the answer is (c).





Figure 19: Examples of VisNumBench and the results predicted by Gemini2.0 Flash (VisNumBench-Real, Quantity, 10/12).

Real (Depth)



Prompt:

Question: The distance from point B to the viewer is X times than point A, Which of the following options is a reasonable estimate for X?

Options: (a) 2.0 (b) 3.1 (c) 5.3 (d) 6.7

Please think and answer the question based on the

most likely options.

Type: Multiplicative Estimation

Answer: (a) 2.0

Gemini 2.0 Flash:

Based on the image, point B looks to be approximately 3 times farther away than point A.So the answer is (b) 3.1

Real (Depth)



Prompt:

Question: Four points are circled on the figure, labeled by A, B, C and D beside each circle. Which of the following options is most likely to be the order in which these points are located from closest to farthest from the viewer?

Options:(a) ACDB (b) BCAD (c) ACBD (d) CBAD Please think and answer the question based on the most likely options.

Type: Value Comparison

Answer: (d) CBAD

Gemini 2.0 Flash:

Okay, let's analyze the image to determine the most likely order of the points from closest to farthest.* **C:** This point is on the building that is on the right-hand side of the image. The building is close to the viewer. Therefore, it's likely that C is the closest point to the viewer.* **A:** This point is on the lamppost which is closer than the buildings at the back.* **B:** This point is on the bell tower further away from the building on the right. It appears farther than the right building with point C.* **D:** This point is near the upper part of the building where point C is located. However, given its position in the image and its relative height, it is more likely to be in the far background, behind the B.Therefore, the most likely order from closest to farthest is C, A, B, D, which corresponds to option **(c) ACBD**.





Figure 20: Examples of VisNumBench and the results predicted by Gemini2.0 Flash (VisNumBench-Real, Depth, 11/12).

Real (Volume)



Prompt:

Question: The total capacity of the bottle is 1500 ml. Which of the following options is a reasonable estimate of the volume of water in the bottle?

Options: (a) (350, 450) ml (b) (1305, 1405) ml (c) (1450, 1550) ml (d) (1050, 1150) ml

Please think and answer the question based on the most likely options.

Type: Range Estimation

Answer: (b) (1305, 1405) ml

Gemini 2.0 Flash:

Based on the image, the water bottle appears to be about 25-30% full. Given a total capacity of 1500 ml, the volume of water is likely between 375 ml and 450 ml. Therefore, the most reasonable estimate is (a) (350, 450) ml.

Real (Volume)



Prompt:

Question: The volume of the right object is X times greater than that of the left object. Which of the following options is a reasonable estimate for X? Options:(a) 3.1 (b) 5.2 (c) 2.0 (d) 6.6

Please think and answer the question based on the most likely options.

Type: Multiplicative Estimation

Answer: (c) 2.0

Gemini 2.0 Flash:

Based on visual estimation, the right object (the Thermos box) appears to be roughly 5 times larger in volume than the left object (the DJI Osmo Pocket 3 box). Therefore, the answer is (b) 5.2.





Figure 21: Examples of VisNumBench and the results predicted by Gemini2.0 Flash (VisNumBench-Real, Volume, 12/12).