NTSEBENCH: Cognitive Reasoning Benchmark for Vision Language Models

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Abstract

Cognitive textual and visual reasoning tasks, including puzzles, series, and analogies, demand the ability to quickly reason, decipher, and evaluate patterns both textually and spatially. Due to extensive training on vast amounts of human-curated data, large language models (LLMs) and vision language models (VLMs) excel in common-sense reasoning tasks, but still struggle with more complex reasoning that demands deeper cognitive understanding. We introduce NTSEBENCH, a new dataset designed to evaluate cognitive multimodal reasoning and problem-solving skills of large models. The dataset contains 2,728 multiple-choice questions, accompanied by a total of 4,642 images, spanning 26 categories. These questions are drawn from the nationwide NTSE examination in India and feature a mix of visual and textual general aptitude challenges, designed to assess intelligence and critical thinking skills beyond mere rote learning. We establish baselines on the dataset using state-of-the-art LLMs and VLMs. To facilitate a comparison between open-source and propriety models, we propose four distinct modeling strategies to handle different modalities—text and images—in the dataset instances.

1 Introduction

Aptitude and reasoning tests have been essential for assessing intelligence and are considered strong indicators of problem-solving ability and abstract reasoning skills (Stern, 1914). Recent advancements in large language models (LLMs) have demonstrated their strong performance on IQ test questions, achieving high scores across many languages (King, 2023). These results indicate that LLMs are advancing toward pseudo human-like intelligence, particularly in text and language tasks.

The capabilities of LLM models rivals humans on various tasks—question answering (QA), sentiment classification, text generation, visual QA, coding challenges, and mathematical reasoning, to name a few (Srivastava et al., 2022; Bubeck et al., 2023). LLMs and VLMs (also known as Multimodal Large Language Models, MLLMs) have hence become the default benchmark for many zero or few-shot text and vision-based tasks (Brown et al., 2020; Wei et al., 2022). Training on vast datasets from diverse domains has enabled LLMs to achieve human-level performance in SAT, GRE, and AP exams, and on platforms such as LeetCode (Achiam et al., 2023; Touvron et al., 2023; Dubey et al., 2024).

The results from King (2023) indicate that LLMs excel in tasks involving textual reasoning such as comprehension, analogies, and identifying opposites but struggle with other types of questions. Multimodal Large Language models have demonstrated remarkable performance in many tests of human intelligence, but they still fall short of human baselines in tasks that require critical and logical thinking, such as commonsense-, numerical- and scientific-reasoning, puzzles, and analogies. Most existing visual and multimodal reasoning datasets are domain-specific, concentrating on fields such as science, engineering, and medicine (Yue et al., 2024; Zhang et al., 2024b; Sun et al., 2024). These datasets primarily focus on tasks related to con-

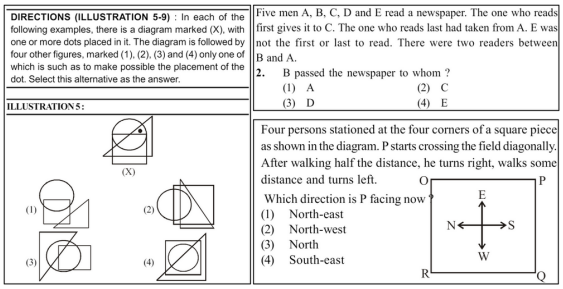

Figure 1: NTSEBENCH **Examples**: Three samples of textual, direction, and spatial reasoning questions from the proposed dataset. Solutions to these questions are not included here but are provided in the dataset.

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crete scenarios or specific domains, often requiring domain knowledge and rote learning for high performance. However, they do not adequately assess intelligence as a function of cognitive/critical reasoning skills such as spatial recognition, visual puzzle solving, abstract reasoning, or pattern recognition. In this study, we aim to address this research gap by introducing a novel benchmark dataset, NTSEBENCH, specifically created to evaluate the complex visual, textual, and multimodal cognitive reasoning capabilities of large deep learning models. Examples of questions from the proposed dataset are shown in Figure 1.

NTSEBENCH is dedicated to establishing a benchmark for testing capabilities that do not rely on domain-specific knowledge or rote learning. Its primary contribution lies in evaluating the innate problem-solving skills inherent in human cognitive development and isolating where models are lacking by presenting well-categorized data. It comprises questions sourced from the Nationwide Talent Search Examination (NTSE) conducted in India. These questions can be presented in text format, visual format, or both (multimodal). We evaluate the performance of recent LLMs and VLMs, including both proprietary (Achiam et al., 2023; Reid et al., 2024) and open-source models (Achiam et al., 2023; Touvron et al., 2023; Jiang et al., 2024a; Wang et al., 2023a; Bai et al., 2023; Li et al., 2024; Lu et al., 2024) on our dataset and perform in-depth error analysis of LLM responses to pinpoint areas of weakness and evaluate their overall robustness. Our work makes the following contributions:

- NTSEBENCH, a dataset to evaluate complex textual, visual, and multimodal cognitive reasoning capabilities with 2,728 questions in 26 problem categories.
- Establish baselines using a diverse range of state-of-the-art LLMs and VLMs on the proposed dataset, incorporating both open-source and proprietary models.
- Assess performance using various modeling strategies to effectively handle multimodal (multi-image inputs as well) inputs for reasoning-based questions.

Code and dataset for the experiments with NTSEBENCH are available at https://ntsebench.github.io/.

2 NTSEBENCH Benchmark

NTSE Exam. The National Talent Search Examination (NTSE), administered by the National Council of Educational Research and Training (NCERT) in India since 1963, is a nationwide exam for secondary-grade students. The exam consists of two sections designed to assess a wide range of analytical skills: the Mental Ability Test (MAT) and the Scholastic Aptitude Test (SAT). The MAT section evaluates students' general aptitude, critical thinking, logical and spatial reasoning, and analytical problem-solving skills (for both textual and visual problems). In contrast, the SAT assesses their domain-specific knowledge in science and mathematics. All questions in the NTSE are multiple-choice (MCQ) with one correct option. Questions and options can be text or image or a combination of both, i.e., multimodal. Our aim is to create a dataset focused to test cognitive reasoning abilities (or MAT-type questions).

Cognitive Reasoning. Cognitive understanding in the context of NTSEBENCH refers to the ability to process information, recognize patterns, draw inferences, and solve problems using critical, logical, and analytical reasoning. This aligns with fundamental concepts in cognitive science, such as problem-solving, pattern recognition, and inferential reasoning (Wang and Chiew, 2010). It encompasses advanced reasoning skills typically found in a small subset of the population, generally individuals with very high IQs. To emphasize this distinction, we use the term *cognitive reasoning* for our dataset, differentiating it from common sense reasoning tasks (Sakaguchi et al., 2021; Talmor et al., 2019). NTSEBENCH assesses these reasoning abilities through diverse question categories, targeting a different cognitive dimension:

- **Pattern Recognition**: Categories such as Series (Numerical, Alphabetical, Alphanumeric), Missing Character, Non-verbal Series, and Dot Problem test the ability to identify and extend patterns, which is crucial for understanding sequences and predicting outcomes.
- **Logical Deduction**: Blood Relation, Syllogisms, Statement and Conclusions, and Data Sufficiency categories focus on making inferences and drawing conclusions based on the given information, reflecting the core of logical reasoning.
- **Spatial Reasoning**: Direction Sense, Cube and Dice, Paper Folding and Cutting, and Embed-

ded Figure assess the ability to visualize and manipulate objects in space, which is essential for understanding spatial relationships.

- **Relational Reasoning**: Analogy and Non-verbal Analogy categories evaluate the understanding of relationships between items and the ability to transfer this understanding to new contexts, a key component of relational reasoning.
- **Quantitative Analysis**: Number and Ranking, Mathematical Operations, Time and Clock, and Figure Partition test numerical problem-solving skills and the ability to manage quantitative data.
- **Classification and Categorization**: Classification/Odd One Out, Non-verbal Classification/Odd One Out categories measure the ability to group items based on shared attributes and identify outliers, highlighting skills in distinguishing unique characteristics and grouping.
- **Contextual Interpretation**: Looking for specific details, instructions, or constraints that are critical to understanding and solving the problem.
- **Verbal Reasoning**: Understanding semantic relationships, word meanings, and analogies.

Unlike other benchmarks that focus on specific academic domains or individual cognitive dimensions as stated above, NTSEBENCH emphasizes a wide range of cognitive skills, offering a more comprehensive assessment of reasoning abilities.

2.1 Dataset Sources

We created the dataset using past NTSE papers and solutions from Resonance. Additionally, we used NTSE preparation materials, such as a reference book titled *A Modern Approach to Verbal and Non-Verbal Reasoning*, which includes additional logical reasoning problems. We also incorporated content from another book titled *Study Guide for NTSE* to construct our dataset. The question extraction process is detailed in Appendix A.1.1. The example questions of the released test dataset in Figure 1 and Appendix B.

Problem Categories: NTSEBENCH encompasses several problem categories, each designed to test a distinct set of skills. Questions from these categories frequently appear in NTSE exams year after year. A detailed description of each category is done in Appendix Table 5 and examples are shown in Appendix section B. More dataset related information is present in Appendix section A.1.

Text Only		Vision + Text	
Categories	**# Samples**	**Categories**	**# Samples**
Series	256	Non-Verbal Series	95
Alphabet Test	94	Missing Character	127
Odd one out	170	Embedded Figure	96
Analogy	151	Non-Verbal odd one out	70
Coding-Decoding	149	Non-Verbal Analogy	100
Number and Ranking	139	Paper Folding & Cutting	96
Blood Relation	126	Incomplete Figure	94
Mathematical Operations	99	Figure Partition	71
Puzzle Test	95	Cube and Dice	89
Syllogisms	44	Dot problem	23
Statement & Conclusions	104	Direction Sense	96
Data Sufficiency	90	Time and Clock	51
		Mirror, Water and Images	92
		Venn diagrams	111

Table 1: **NTSEBench categories count**: Problem categories with different input modality types and number of samples for each.

Table 1 shows a skewed distribution across various question categories. Notably, textual categories such as the Alphabet Test (ALP) and Mathematical Operations (MTO) contain 94 and 99 examples, respectively. In contrast, many vision-based categories are more challenging and typically include between 80 and 100 examples. For instance, the Non-Verbal Analogy (NVA) category, one of the most difficult, comprises 100 examples. Although this skewed distribution could impact model performance, exploring its effects is beyond the scope of this manuscript and is left for future work.

Modality Variations. Since NTSEBENCH has multimodal questions, options, and solutions, we have results in eight combinations of modality types that can occur for question-options-solution triplet. Table 2 shows the count of each triplet option. NTSEBENCH has 1199 textual questions and the remaining 1529 are multimodal questions.

Question	Options	Solutions	# Samples
✗	✗	✗	1199
✗	✗	✓	381
✗	✓	✗	70
✗	✓	✓	18
✓	✗	✗	330
✓	✗	✓	126
✓	✓	✗	403
✓	✓	✓	201

Table 2: NTSEBENCH **Modality Variations Question Count**: Tick(✓) mark indicates whether question, option or solution contains image.

2.2 The Global Relevance of the NTSE Exam for AI

The NTSE exam, despite being conducted in India, holds significant relevance for the global AI community due to its unique focus on cognitive reasoning abilities rather than domain-specific knowledge. The NTSE's diverse question categories as

described in Table 1(and Appendix table 5), assess various cognitive dimensions, offering a robust framework for evaluating AI models' capacity to process information, recognize patterns, and solve problems across different domains. This emphasis on cognitive dimensions aligns with the pursuit of Artificial General Intelligence (AGI), making the NTSE exam's insights and challenges applicable to AI research and development on a global scale.

3 Models: LLMs and VLMs

Problem Formulation. Consider a single (i^{th}) instance in the dataset is represented by D_i=(Q_i^J,O_i^J,S_i^J), where Q represents the questions, O represents the options of the MCQ, and S represents the solution to the question. $J \in (T, I)$ represents the modality type, which can be either text(T) or image(I).

Modeling Strategies. Evaluating the reasoning abilities of large language models (LLMs) with text-based questions is straightforward. For vision-language models (VLMs), reasoning with vision-text questions is generally not straightforward. Some API access model models, such as GPT-4o (Achiam et al., 2023) and Gemini (Reid et al., 2024), support multi-image inputs, but many others do not (open-source models like LLaVA-OneVision (Li et al., 2024) and Ovis (Lu et al., 2024) are emerging with this capability). To address these task-specific and input-related dependencies, we propose four strategies to fairly evaluate the reasoning abilities of both open-source and proprietary models.

- ***Standard QA.*** For instances where question type(J) for questions(Q), options(O) and solutions(S) is text(T), we use a standard text-based QA model such as GPT3.5-Turbo or Llama3-70b (AI@Meta, 2024) or Mixtral8x7b (Jiang et al., 2024a).

- ***Image-Only.*** We propose a modeling approach where questions and all the options are presented to the model as a single image. This image consolidates all relevant textual and visual content exactly as it appears in the examination paper, effectively capturing the entire question, including both textual and visuals. This strategy utilizes the OCR capabilities of VLM models to interpret and analyze the content, enabling them to process both text and visual elements within the same input (Shi et al., 2023; Fujitake, 2024; Zhao et al., 2023). The key advantage of this approach is its applicability across all modality types.

- ***Interleaved model.*** In this approach, we integrate text with multiple images to create an interwoven context. This method involves placing related textual and visual elements in proximity, enhancing the model's ability to draw connections.

- ***Standard VQA.*** Open-source models typically lack the capability to integrate text and images within a single prompt. To enable fair comparisons, we propose an alternative modeling strategy where the question and option images are combined into a single composite image, labeled as Figure 1, Figure 2, etc. This composite image is accompanied by a structured textual prompt that describes different parts of the image, directing the model's attention to relevant visual details. The composite image and prompt are then used to evaluate the model's performance, testing its ability to interpret and respond to questions based on the integrated visual and textual information.

Example inputs for each of the above modeling strategy proposed are shown in Appendix Figure 3.

Prompting Strategies. We mainly employed two main prompting strategies for setting up all the baselines on the proposed dataset: (A) **Zero Shot COT**: The model is presented with a prompt that includes a question and a set of answer options. It is tasked with selecting the correct option and providing an explanation that justifies its choice. (B) **Few Shot COT**: In few-shot chain-of-thought (COT) prompting, a set of N exemplar triplets—each containing a question, options, and a solution (D_i)—is included in the prompt before presenting the test question. The number of exemplars N is selected based on the token limit supported by the model.

Implementation Details. We evaluate NTSEBENCH using multiple open-source and proprietary LLMs (Achiam et al., 2023; Touvron et al., 2023; Team et al., 2023) and VLMs (Reid et al., 2024; Bai et al., 2023; Dong et al., 2024; Wang et al., 2023a). We used a low temperature setting to promote reproducibility. Details on models used and their hyperparameters can be found in Appendix A.4.

In the few-shot settings, the questions were sorted by solution length, and then an annotator picked the three examples with the most comprehensive responses.

Answer Extraction and Evaluation. The answer extraction module uses a rule-based approach to identify the correct option from the response (Gupta et al., 2023). Responses where the answers cannot be extracted by module are evaluated by humans. We used percentage accuracy as our **metric for evaluation** across all the models. If the model chooses the right option in the MCQ question, label is set as TRUE, else label is FALSE.

Option Bias Ablation. We conducted option shuffling experiments to assess whether model performance is influenced by the position of the correct option and to detect potential bias. Four dataset variations were created, placing the correct answer in positions 1, 2, 3, and 4, respectively. Each experiment was run in three rounds, and results were averaged to ensure robustness.

4 Results and Analysis

Our experiments answer the following questions:

- How well do LLMs and VLMs perform on advanced textual, visual, and multimodal reasoning questions? How challenging is cognitive reasoning for the current state-of-the-art models?
- Are proprietary models superior to open-source models, and if so then by what margin? Are there specific categories where proprietary models significantly outperform open-source models?
- Do different modeling strategies affect a model's accuracy? Does OCR impact the reasoning accuracy of models?
- Does shuffling the options in questions impact model performance, indicating a potential option bias in large models?

Results for text-only questions using ***Standard QA*** and ***Image Only*** (implicit OCR) modeling strategy are shown in Table 3. For the ***Standard QA*** strategy, we report results for zero shot setting in all 10 models listed in the appendix A.4. For ***Image Only*** modeling, results are reported for five models that support vision or multimodal inputs for zero shot results. Columns in the table refers to different types of questions in NTSEBENCH such as SER (series), ALP (alphabet Test), ODO (odd one out), ANA (analogy), COD (coding-decoding), NUM (number and ranking), BLR (blood relation), MTO (mathematical operations), PUZ (puzzle test), SYL (syllogisms), STC (statement and conclusions), and DAT (data sufficiency).

Results for the multimodality questions are reported in Table 4. Results are reported using three modeling strategies listed in the section above namely ***Interleaved, Image Only*** and ***Standard VQA***. Columns in the table refer to different categories of visual text reasoning questions in NTSEBENCH such as DIR (direction sense), VEN (venn diagrams), TIM (time and clock), MIS (missing character), NVS (non-verbal series), NVO (non-verbal odd one out), NVA (non-verbal analogy), INC (incomplete figure), MIR (mirror, water and images), CUB (cube and dice), PAP (paper folding and cutting), EMB (embedded figure), FIG (figure partition), DOT (dot problem). Option bias ablation results for Gemini-1.5-pro and GPT-4o models are shown in Appendix Tables 8, 9, 10, and 11. **Proprietary models outperform open-source models.** From results in Table 3 and 4, we can observe that proprietary models, such as Gemini Pro 1.5, GPT-4o and o1-preview, outperform other open-source models in nearly every question category, especially o1-preview, which operates by utilizing internal chain-of-thought reasoning, allowing it to analyze complex problems step-by-step before arriving at a solution. Proprietary models demonstrate nearly double the accuracy of open-source models on NTSEBENCH questions, both in text-based and multimodal tasks, across all modeling strategies outlined in the previous section. Notably, Gemini Pro 1.5 consistently outperforms GPT-4o across most strategies, excelling in both text and multimodal question types.

For open-source models, LLaVA-OneVision-72b-ov-chat excels in text and multimodality tasks, achieving SOTA results on tasks such as Non-verbal Odd One Out and Embedded Figure, also matching or surpassing proprietary models in several other categories. Ovis1.6-Gemma2-9B, although smaller, outperforms GPT-4o and LLaVA-OneVision in several vision categories, but its overall performance is still lower.

Modeling Strategy is important. For text-only questions, the ***Standard QA*** strategy clearly outperforms ***Image Only*** modeling. Introducing the burden of doing OCR on top of reasoning tends to confuse models or exacerbate the difficulty of the task. This effect is particularly noticeable with smaller open-source models, which struggle to accurately extract characters and integrate them into context. However, proprietary models such as GPT-4o and Gemini-Pro still achieve superior results us-

	Model	SER	ALP	ODO	ANA	COD	NUM	BLR	MTO	PUZ	SYL	STC	DAT	Avg. Per
	Image Only													
Zero Shot	CogVLM-2	14.84	17.02	20.00	19.87	24.83	16.55	23.81	20.20	20.00	22.73	22.12	15.56	19.79
	InternLM-XComposer2	18.36	18.09	21.76	16.56	17.45	11.51	15.87	24.24	25.26	11.36	17.31	8.89	17.22
	Qwen-VL-Chat	29.69	23.4	26.47	23.84	27.52	23.19	18.25	26.26	30.53	6.82	15.38	21.59	22.74
	Gemini 1.5 Pro	**32.42**	**31.91**	47.65	**52.32**	27.52	**37.41**	38.10	29.29	**47.37**	**47.73**	38.46	**44.44**	**39.55**
	GPT-4o	28.12	**31.91**	49.41	45.03	30.87	32.37	**52.38**	**34.34**	36.84	43.18	**53.85**	33.33	39.30
Few Shot	*Gemini 1.5 Pro*	23.32	23.08	46.11	47.97	24.66	36.76	36.59	32.29	42.39	31.71	32.67	22.99	33.37
	GPT-4o	32.02	29.67	**50.30**	42.57	**32.19**	35.29	43.09	25.00	46.74	41.46	53.47	34.48	**38.85**
	Standard QA													
Zero Shot	Mixtral-8x7B	19.76	19.57	24.71	45.52	14.77	26.09	29.37	29.59	32.93	24.32	53.85	33.33	29.48
	Llama-3 70B	35.18	26.09	47.65	57.93	36.36	36.23	50.79	31.63	60.98	54.05	52.88	40.48	44.18
	GPT-3.5 Turbo	35.97	32.61	40.00	51.72	36.36	25.36	36.51	27.55	46.34	35.14	40.38	32.14	36.67
	CogVLM-2	22.27	21.28	27.65	34.44	22.82	18.71	30.95	19.19	29.47	18.18	28.85	27.78	25.13
	InternLM-XComposer2	21.88	24.47	19.41	36.42	25.50	28.78	25.40	27.27	45.26	40.91	34.62	28.89	29.90
	Qwen-VL-Chat	30.08	18.09	23.53	31.13	26.85	15.11	24.6	27.27	28.26	13.64	15.38	24.44	23.19
	Gemini 1.5 Pro	63.67	39.36	60.00	**69.54**	**61.07**	68.35	58.73	45.45	**81.05**	**65.91**	70.19	**63.33**	**62.22**
	GPT-4o	42.58	35.11	55.88	65.56	38.26	42.45	68.25	41.41	69.47	63.64	70.19	43.33	53.01
	LLaVA-OneVision	42.19	32.98	50.59	57.62	45.64	36.69	57.94	37.37	64.21	50	62.5	46.67	48.7
	Ovis1.6-Gemma2-9B	42.58	31.91	50	50.99	42.95	46.04	38.89	31.31	53.26	27.27	55.77	33.33	42.025
Few Shot	Mixtral-8x7B	27.20	24.72	28.14	50.70	29.41	27.41	33.33	29.47	18.99	#	55.45	32.10	32.44
	Llama-3 70B	34.00	16.85	44.91	51.41	36.47	34.81	39.84	32.63	34.18	#	50.50	34.57	37.28
	GPT-3.5 Turbo	30.80	32.58	20.96	47.89	30.59	31.11	30.08	29.47	36.71	#	40.59	34.57	33.21
	Gemini 1.5 Pro	**63.24**	37.36	**59.28**	68.92	60.27	**68.38**	58.54	43.75	80.43	63.41	70.30	62.07	**61.32**
	GPT-4o	42.29	**40.66**	58.08	67.57	44.52	40.44	**69.92**	**46.88**	72.83	63.41	**71.29**	*	56.17
	Advanced Reasoning Models													
	OpenAI o1-preview	80.62	90.22	84.05	73.13	85	85.83	83.61	83.7	84.81	81.08	72.28	83.33	**81.88**

Table 3: **Text Only Question Results.** Zero-shot and few-shot performance of different models across various *text-only* categories. We report results using two modeling strategies *Image Only* and *Standard QA*. *italics* font for propriety models, i.e., money or API access is required to run these models. The # is due to the category's solution contains images thus restricting few shot on text-only models. Note: (*) In some models, a common issue arises when a model refrains from providing a response due to safety concerns, often stemming from misinterpretation of the image's intent, e.g., thinking it as CAPTCHA.

ing ***Image Only*** compared to open-source models employing ***Standard QA*** or text-only processing alone. Few-shot results present a mixed picture: where as models like Mixtral and GPT-4o show improved performance with added exemplars, others experience a significant decline. Tables 3 and 4 show that proprietary models generally experience a smaller performance drop than open-source models in such scenarios.

Interleaving text and images performs better than ***Standard VQA*** and ***Image Only*** strategy for most categories. This underscores the importance of presenting text and images separately and in a more detailed manner, providing appropriate context, and treating the image and text as distinct entities. Our results in Table 4 show that this approach significantly improves VLM results, as demonstrated by the superior performance of open-source models such as LLaVA-OneVision-72b and Ovis-9b, which handle interleaved text and images more effectively than others. Table 4 also shows that few-shot prompting consistently underperforms compared to zero-shot for all VLM models, suggesting that adding exemplars may confuse VLMs, hindering their focus on logical reasoning.

Multimodal reasoning is significantly harder. Comparing the best and worst performing models in Tables 3 and 4, it is evident that multimodal reasoning is considerably more challenging than textual reasoning for current state-of-the-art models. Multimodal questions see less than 45% accuracy, whereas the best model for textual reasoning, o1-preview, exceeds 80%. Even fast models such as Gemini 1.5 pro achieve over 60% accuracy in textual reasoning, highlighting the gap between VLMs and LLMs and the need for better architectures and datasets for VLMs.

Question category analysis. The results from Table 3 reveal that even though LLMs generally perform better on the text-only subset of NTSEBench, the high standard deviation (11.04) indicates significant variability in model performance across different question types. This variability may stem from some overlap between NTSEBench and other open-source datasets, suggesting that there are still areas where LLMs ex-

	Model	DIR	VEN	TIM	MIS	NVS	NVO	NVA	INC	MIR	CUB	PAP	EMB	FIG	DOT	Avg. Prec.
	Interleaved															
Zero Shot	Qwen-VL-Chat	28.12	19.82	19.61	12.6	22.11	27.14	22.00	23.40	27.17	15.73	23.96	30.21	8.45	17.39	21.26
	Gemini 1.5 Pro	**63.54**	**64.86**	**70.59**	**37.01**	**33.68**	25.71	**32**	**38.3**	**35.87**	**43.82**	30.21	36.46	**46.48**	**30.43**	**42.06**
	GPT-4o	37.50	50.45	41.18	29.92	16.84	22.86	26	23.4	34.78	35.96	27.08	22.92	45.07	17.39	30.81
	LLaVA-OneVision	27.27	39.64	44.44	32	14.74	**28.57**	26	26.6	32.61	36.59	26.04	**37.5**	33.8	26.09	30.85
	Ovis1.6-Gemma2-9B	35.42	36.04	39.22	23.62	25.26	28.57	19	32.98	32.61	10.11	29.17	23.96	9.86	21.74	26.25
Few Shot	*Gemini 1.5 Pro*	62.37	63.89	68.75	36.29	31.52	23.88	29.9	36.26	33.71	41.86	27.96	34.41	44.12	20	**39.63**
	GPT-4o	39.78	52.78	52.08	27.42	17.39	*	*	19.78	*	38.37	**33.33**	*	41.18	*	35.79
	Image Only															
Zero Shot	CogVLM-2	18.75	18.02	25.49	14.96	18.95	20	8.00	12.77	7.61	19.10	16.67	12.50	12.68	4.35	14.98
	Qwen-VL-Chat	21.05	26.13	27.45	22.22	**26.32**	21.43	17.00	21.28	19.57	25.84	25	18.75	18.31	17.39	21.98
	InternLM-XComposer2	20.83	20.72	15.69	17.32	15.79	11.43	10.00	14.89	8.70	19.10	10.42	11.46	22.54	8.70	14.82
	Gemini 1.5 Pro	**52.08**	**37.84**	**49.02**	25.2	24.21	24.29	27	**26.6**	**29.35**	32.58	23.96	23.96	**42.25**	**34.78**	**32.36**
	GPT-4o	40.62	31.53	33.33	22.05	22.11	**25.71**	19	24.47	23.91	26.97	**34.38**	23.96	**42.25**	21.74	28.00
Few Shot	*Gemini 1.5 Pro*	47.31	27.78	33.33	**29.03**	25.00	23.88	21.65	23.08	21.35	**37.21**	32.26	19.35	22.06	25.00	**27.73**
	GPT-4o	31.18	29.63	37.50	22.58	23.91	14.93	**23.71**	21.98	21.35	23.26	26.88	**26.88**	39.71	20.00	25.96
	Standard VQA															
Zero Shot	CogVLM-2	15.62	12.61	29.41	11.02	8.42	4.29	6	3.19	11.96	15.73	9.38	10.42	8.45	17.39	11.70
	Qwen-VL-Chat	21.88	18.92	27.45	5.51	23.16	22.86	20	24.47	**26.09**	8.99	20.83	19.79	8.45	8.7	18.36
	InternLM-XComposer2	25	20.72	25.49	17.32	18.95	8.57	15	5.32	16.3	12.36	20.83	10.42	12.68	13.04	15.85
	Gemini 1.5 Pro	54.17	**49.55**	62.75	**37.8**	24.21	24.29	21	**29.79**	21.74	**46.07**	23.96	23.96	40.85	**26.09**	**34.73**
	GPT-4o	50	45.95	39.22	28.35	**32.63**	**25.71**	**26**	18.09	22.83	40.45	23.96	**28.12**	40.85	**26.09**	32.01
Few Shot	*Gemini 1.5 Pro*	**61.29**	47.22	**68.75**	32.26	17.39	16.42	18.56	27.47	20.22	44.19	20.43	25.81	**44.12**	25	**33.50**
	GPT-4o	41.94	49.07	45.83	27.42	15.22	23.88	22.68	15.38	25.84	34.88	**26.88**	22.58	35.29	25	29.42

Table 4: **Multi-modality Question Results**: Zero-shot and few-shot performance of different VLMs across various Text+Vision categories. We report results using all three different modelling strategies proposed to handle multimodality data, i.e., *Interleaved*, *Image Only* and *Standard VQA*. *italics* font for proprietary models, i.e., money or API access is required to run these models. Note: (*) In some models, a common issue arises when a model refrains from providing a response due to safety concerns, often stemming from misinterpretation of the image's intent, e.g., thinking it as CAPTCHA.

hibit limitations in reasoning capabilities. This is especially evident in Alphabet Test (ALP) category and Mathematical Operations (MTO) category, where the accuracy is more than two standard deviations away from the mean accuracy of the model. This could also be attributed to the potential difficulty of these question types; however, that analysis has been left for future work.

VLMs have shown poor performance across all categories for multimodal questions, with the best-performing model achieving correct answers only 42% of the time. Even the standard deviation for accuracy of the best model is 9, indicating that VLMs struggle more with certain question categories than others. Specifically, we observe that VLMs perform notably poorly on categories such as DOT (Dot Problems), NVS (Non-verbal Series), and NVO (Non-verbal Odd One Out). These categories require identifying correlations or patterns between multiple images or recognizing emerging patterns in a sequence of images. This task is akin to identifying similar and evolving patterns in different parts of an image and predicting the next possible pattern. Although vision models excel at recognizing existing patterns, they struggle with predicting new patterns.

NTSEBENCH **presents a challenging task for SOTA LLMs and VLMs**. Based on the findings in Tables 3 and 4, it is evident that the proposed dataset presents a challenging task for all state-of-the-art LLM and VLM models. None of the open-source models achieve accuracy exceeding 50% on text-only questions and 35% on multimodal questions, with proprietary models achieving 62% and 42% accuracy, respectively. Although o1-preview is categorized in a separately, it got more than 80% accuracy on text-only data, it cannot do multimodal reasoning. Many of the models tested did not even reach random selection/guess baseline of 24.52% (261 question had 5 options and 2467 question has 4 options), indicating that current LLMs and VLMs struggle with cognitive reasoning questions.

Human vs Model. Preliminary human evaluation results shown in appendix section A.3.1 show that average human accuracy for textual and multimodal questions is more than 80%, much greater than 62% (text) and 42% (visual) for best performing propriety model. Although the o1-preview

model have achieved near human accuracy on textual reasoning, it is significantly slower than other models. These findings suggest potential for future advances in tackling diverse textual and visual reasoning questions.

Options Bias Ablation. From Gemini 1.5 Pro Results in Table 8 and 9 we can see that aggregate performance for both multimodal and text question is affected by the position of the correct option (variation in performance ranging from -4 to +6 percent when compared to random for text and -5 to +5 percent for multimodal categories). We can make a similar observation on GPT-4o (Tables 10 and 11); however, GPT-4o has smaller variation in performance than Gemini Pro. These variations suggest that the model's responses to logical questions may be either memorized or guessed, indicating a potential limitation in LLMs and VLMs. Even o1-preview, as shown in Table 12, exhibits performance variations akin to those of GPT-4o, suggesting that advanced reasoning models are similarly affected by bias.

Error Analysis. We manually conducted an error analysis of 260 questions (10 from each question category) for Gemini 1.5 pro, and we identified distinct patterns in reasoning and error categorization. We have categorised errors based on the cognitive dimensions outlined in section 2. The Sankey diagram in Figure 2 illustrates how errors across various question categories correspond to specific error types. A key observation is that many errors arise from **Pattern Recognition** failures, especially in categories like *Alphabet Tests, Non-verbal Analogy, and Series* questions, where the model struggled with recurring patterns and sequence shifts, highlighting challenges in complex pattern-based reasoning. We also noted frequent errors in **Spatial Reasoning** and *Logical Deduction* tasks, particularly in spatial or diagrammatic questions such as *Cube and Dice, Embedded Figure, and Paper Folding and Cutting*. These questions often require pattern recognition, shape manipulation, or deducing logical relations from limited visual data. The figure also shows that errors in **Quantitative Analysis** were common in numerical questions such as *Time and Clock* and *Mathematical Operations*, indicating the model excels in simpler tasks but struggles with complex number sequences and operations. The error distribution reveals key insights into the model's strengths and weaknesses, guiding future improvements. A detailed error analysis for each category is included in Appendix A.2.

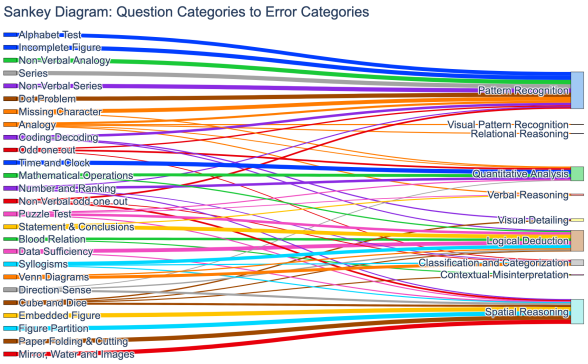

Figure 2: **Error Analysis.** Overview of errors Gemini 1.5 Pro makes across different question categories.

5 Related works

Texual and Multimodal Reasoning datasets. There exist multiple datasets to test domain specific textual (math, science, medicine) QA and reasoning abilities of LLMs and VLMs knowledge such as SciBench (Wang et al., 2023b), SciEval(Sun et al., 2024), MMMU (Yue et al., 2024), MathVista (Lu et al., 2023), JEEbench (Arora et al., 2023), MathVerse (Zhang et al., 2024a), OlympiadBench (He et al., 2024) and many others based on real-world images or other domains (He et al., 2020; Soni et al., 2022; Liu et al., 2023; Thrush et al., 2022; Li et al., 2023). Even most existing visual and multimodal reasoning datasets in the literature are domain-specific M3Exam (Zhang et al., 2024b), RAVEN (Zhang et al., 2019), or they involve reasoning about real-world images (Liu et al., 2023; Wang et al., 2024; Thrush et al., 2022; Li et al., 2023) with basic common sense reasoning questions such as CLEVR (Johnson et al., 2017). However, current research has not thoroughly explored the capabilities of large models in addressing cognitive/critical reasoning problems for both textual and multimodal data. NTSEBENCH is different from all already existing datasets in the literature because it explicitly focuses on testing cognitive reasoning abilities of large deep learning models. Although benchmarks like BBH (Suzgun et al., 2022) focus on text-based logical deduction and direction sense, NTSEBENCH offers a more holistic assessment by integrating both textual and visual elements. For example, it includes categories that combine text with visual answers, such as Venn diagrams and figure partition questions, which BBH does not cover. NTSEBENCH also includes areas overlooked by other benchmarks, such as series,

coding-decoding, and blood relations. With 2,728 multiple-choice questions, it provides a broader evaluation than the 770 puzzles in BBH.

Furthermore, benchmarks such as (Jiang et al., 2024b) emphasize visual abstraction and reasoning but lack the integration of text and visual elements found in NTSEBENCH. Our dataset also goes beyond Raven's Progressive Matrices (RPMs) (Zhang et al., 2019) and related visual analogy problems, which are central to Małkiński and Mańdziuk (2023), by incorporating a wider array of cognitive tasks. This includes diverse categories such as coding-decoding, number and ranking, blood relations, and mathematical operations. NTSEBENCH provides a fine-grained analysis of model performance across 26 distinct problem categories and investigates various modeling strategies, setting it apart from other benchmarks. Datasets such as (Wang et al., 2024; Liu et al., 2023; Masry et al., 2022) explore mathematical reasoning in visual contexts but do not permit multiple images in the same prompt or reasoning across images. This is crucial for identifying patterns in categories of NTSEBENCH, such as Paper Folding and Cutting, Embedded Figure, Figure Partition, and Mirror/Water images.

Although ARC (Chollet, 2019) also targets general human cognitive understanding, its questions are primarily focused on visual tasks such as pattern completion, interpolation, denoising, and simple object counting. These tasks are relatively straightforward and often lack the need for complex reasoning. By leveraging NTSE exam questions, our dataset offers real-world relevance and facilitates quantitative evaluation through a multiple-choice format. Additionally, NTSEBench enables fine-grained performance analysis across cognitive dimensions, emphasizing knowledge integration and reasoning, which more closely mirrors human cognitive processes. These attributes make NTSEBench a more comprehensive and effective tool for evaluating AI's cognitive capabilities.

Language Writ Large (Harnad, 2024) delves into the theoretical foundations of large language models (LLMs) like ChatGPT, offering insights into their unexpected capabilities through the analysis of technology dialogues. In contrast, NTSEBench provides quantitative performance metrics for LLMs across a wide range of reasoning tasks. MMMU (Yue et al., 2024), on the other hand, spans six disciplines and 30 college subjects, providing a broad overview of subject-specific knowledge. In contrast, NTSEBench offers a deeper, more focused evaluation of cognitive reasoning skills, making it an essential tool for assessing the reasoning capabilities of LLMs.

Zero shot and few shot prompt engineering for textual and multimodal input. Our work is also related to prompting design and prompt engineering for LLMs (Brown et al., 2020; Chen et al., 2023; Gupta et al., 2023; Khot et al., 2022; Wei et al., 2022; Sahoo et al., 2024; Ali et al., 2024) and VLMs (Xu et al., 2024; Bai et al., 2023; Liu et al., 2024; Dai et al., 2024). There are numerous studies on multimodal and vision Chain-of-Thought (CoT) prompting (Zhang et al., 2023; Shao et al., 2024). These studies overlook the ability of state-of-the-art vision-language models (VLMs) to process multiple images simultaneously, a limitation of older models with smaller context windows. Newer models can handle few-shot examples for CoT prompting, and we explore three prompting strategies enabled by their extended context windows.

6 Conclusion and Future Work

We developed a new dataset, NTSEBENCH, to assess the advanced analytical and logical reasoning capabilities of large deep learning models (LLMs and VLMs). We also propose four distinct modeling strategies for handling multimodal data (text and images) across different question types in NTSEBENCH. These strategies enable us to conduct a fair and comprehensive comparison between proprietary and open-source models using both zero-shot and few-shot scenarios. Our findings show that both LLMs and VLMs struggle with advanced visual reasoning tasks, with VLMs performing worse on multi-modal questions than LLMs on textual ones. Proprietary models also consistently outperform open-source models, correctly predicting twice as many questions. Overall, our results underscore that NTSEBENCH poses significantly greater challenges for state-of-the-art LLMs and VLMs. **Future directions.** (a) Our results indicated that VLM models have difficulty predicting novel patterns, implying that addressing this challenge may involve either architectural modifications or the integration of generative models alongside VLMs for these question types. (b) Given the limited data available for cognitive reasoning questions, we plan to use data augmentation strategies to increase the number of samples.

Limitations

While our dataset is new and sourced for different sources when compared to datasets already present in the literature, there still might be some overlap in reasoning questions, especially in textual reasoning. So all the dataset instances might not be independent and exclusive. This dataset is solely created in English, so no other languages are represented; therefore, we cannot analyze whether language variations can have a significant impact on the reasoning capabilities of these large models. Our modelling strategies were limited to zero-shot and few-shot COT prompting. We did not evaluate whether fine-tuning these large models on a few examples from each of the categories would further improve results. This was due to the limitation of both GPU resources and large cost of fine-tuning for proprietary models. Finally, our human evaluation study involved only three annotators with undergraduate degrees, which may limit the generalizability of the results to the broader human population. We plan to address all these limitations in the future extension of this work.

Ethics Statement

As authors of this work, we affirm that our research adheres to the highest ethical standards in both its conduct and publication. We have carefully considered and addressed various ethical considerations inherent in computational linguistics methodologies to ensure responsible and fair practices. We prioritize transparency by providing detailed information to facilitate the reproducibility of our results. This includes sharing our code and datasets, which are sourced from publicly available datasets and handled in compliance with ethical guidelines established by the original authors. Although our paper accurately reflects our experimental findings, we acknowledge the inherent variability associated with large language models, which we mitigate by maintaining a fixed temperature setting. We provide comprehensive descriptions of our annotations, dataset splits, models used, and prompting methods employed, ensuring the reproducibility of our work. For grammar correction, we utilize AI-based writing assistants, and for coding, we leverage tools such as Copilot. Importantly, the genesis of our research ideas and the execution of our study were entirely independent of AI assistance.

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A Appendix

A.1 Additional Dataset Details

Table 1, reveals a skewed distribution across various question categories. Notably, textual categories like the Alphabet Test (ALP) and Mathematical Operations (MTO) contain 94 and 99 examples, respectively. In contrast, many vision-based categories are more challenging and typically include between 80 and 100 examples. For instance, the Non-Verbal Analogy (NVA) category, one of the most difficult, comprises 100 examples. Although this skewed distribution could impact model performance, exploring its effects is beyond the scope of this manuscript and is left for future work.

Problem Sub categories. The above categories are further subdivided based on the different modality of input type(text or text-vision). Table 1 lists each sub-category for **Text Only** questions and **Text+Vision** questions, along with the respective count for each category. As in Table 1 most categories are represented well in the dataset.

Problem Categories Problem categories in the dataset with description are shown in Table 5.

A.1.1 Data Extraction Pipeline

The questions are extracted from the sources listed in section 2.1, with human intervention to monitor and rectify mistakes made by the automated pipeline. The data extraction pipeline involves first processing the PDF through MATHPIX OCR[1] to generate a Word file, which was then manually corrected for any errors. Next, we used the DOCXLATEX [2] library to convert all equations into LaTeX expressions. Finally, we leveraged the PYMUPDF [3] library to extract all text and images, extracting :

- **(1) Textual data** i.e. direction (extra guidance on the context of the question), the question, the correct answer option and the solution. Any errors in text extraction was rectified by human annotator.

- **(2) Vision Based data** i.e. relevant image/s which we segregate into direction images, problem images, option images, and solution images. Questions associated with low-quality images were excluded. A human annotator assisted in identifying these low-quality images.

[1] MathPix OCR
[2] docxlatex
[3] PyMuPDF

Category	Description
Series	Finding the missing element in numerical, alphabetical, or alphanumeric series.
Alphabet Test	Focusing on operations involving the English alphabet, such as anagrams.
Classification/Odd One Out	Identifying the item that is different from the others.
Analogy	Solving problems of the type a:b::c:?
Coding-Decoding	Deciphering codes and symbols to infer rules and apply them to new examples.
Number and Ranking	Calculating occurrences or determining order based on certain properties.
Blood Relation	Solving problems based on family relationships.
Mathematical Operations	Using mathematical operations like addition, multiplication, subtraction, and division to solve problems.
Direction Sense	Determining direction and location based on given instructions.
Venn Diagrams	Using set theory and relationships depicted in Venn diagrams to solve problems.
Time and Clock	Calculating dates, days, and times based on given information.
Missing Character	Predicting the missing element in a figure, requiring spatial thinking.
Non-Verbal Series	Predicting the next element in a sequence of figures.
Non-Verbal Classification/Non-Verbal Odd One Out	Identifying the figure that is different from the others.
Non-Verbal Analogy	Solving analogy problems of the type a:b::c:? using figures.
Incomplete Figure	Identifying the missing part of a figure.
Mirror, Water and Images	Solving problems related to reflections and image transformations.
Cube and Dice	Solving problems involving painting, counting, and manipulating cubes and dice.
Paper Folding & Cutting	Determining the resulting shape after paper folding and cutting.
Embedded Figure	Finding the alternative which contains a given figure as its part.
Puzzle Test	Solving general puzzles involving arrangement and deduction.
Figure Partition	Calculating the number of specific shapes (like triangles) in a figure.
Dot Problem	Finding similar conditions in alternative figures based on dot arrangements.
Cryptography	Deciphering codes that involve arithmetic operations.
Syllogisms	Making inferences based on given statements, often solved using Venn diagrams.
Statement & Conclusions	Making inferences based on given statements, not typically solved with Venn diagrams.
Data Sufficiency	Determining whether the given information is sufficient to solve a problem.

Table 5: NTSEBENCH **Problem Categories**. This table lists broad categories of problems that frequently appear in the NTSE exam. *Note: This is not an exhaustive list; other types of questions may also appear in the NTSE exam.*

A total of 2,728 MCQ (multiple-choice questions) consisting of a total of 4,642 images across 26 categories of questions are extracted and NTSEBENCH is created along with the necessary metadata.

The correct answers to the questions are also officially provided by the NTSE exam organizers (under NCERT). The exam is renowned for its high quality, as the questions are typically designed by subject-matter experts. Any disputes or challenges regarding incorrect answers or flawed questions are meticulously reviewed by NCERT before the release of the final answer key, ensuring the accuracy and reliability of the solutions, ensuring good quality data.

A.1.2 Dataset Sources Links

(a.) Resonance [4]. (b.) Reference book titled *A Modern Approach to Verbal and Non-Verbal Reasoning* [5]. (c.) Another book titled *Study Guide for NTSE* [6].

A.2 Error Analysis for different question categories

Analyzing the incorrect responses of Gemini 1.5 Pro across different categories highlighted several error patterns and identified key areas for improvement.

Alphabet Test: Common errors involve incorrect word ordering and miscalculated letter positions, resulting in faulty alphabetical arrangements. The model needs improved techniques for letter manipulation and more accurate application of alphabetical rules.

Analogy: The model struggles with identifying underlying relationships in both verbal and non-verbal analogies, often misinterpreting visual patterns. Enhancing pattern recognition, especially in visual contexts, would strengthen performance.

Blood Relation: A frequent issue is the misinterpretation of family relationships, particularly when mapping out complex family trees. Focused improvements in logical reasoning around relational structures can address this.

Odd One Out: Errors often arise from misidentifying the unique element in a set, as the model fails to consistently recognize distinguishing patterns. Better classification based on subtle attribute differences is needed.

Coding-Decoding: Incorrect application of coding schemes, such as letter shifts or reversals, is common. The model also fails to detect important details in coding patterns, highlighting the need for more attention to detail.

Cube and Dice: The model exhibits difficulty with visualizing 3D objects and their geometric properties, leading to errors in counting cube faces or determining surface areas. Spatial reasoning should be strengthened in these cases.

Data Sufficiency: Misinterpretation of the sufficiency of provided statements to solve a problem is

[4] Paper Links
[5] A Modern Approach to Verbal and Non-Verbal Reasoning
[6] Study Guide for NTSE

a frequent error. The model often fails to draw correct conclusions from quantitative data, indicating a need for better assessment and logic application.

Direction Sense: The model often misinterprets movements and directions, leading to incorrect final positions. Quantitative errors also arise in calculating distances or angles, suggesting that spatial reasoning and movement tracking must be enhanced.

Embedded Figure: The model has difficulty recognizing shapes embedded within larger figures, especially when they are rotated. This calls for improved shape recognition regardless of orientation.

Figure Partition: Errors in counting the components of complex figures, such as lines or triangles, often occur due to difficulty visualizing accurate partitioning. Improved counting strategies and partitioning techniques are needed.

Incomplete Figure: The model misidentifies the missing part of a figure due to incorrect application of rotation or pattern recognition. Enhancing geometric transformation abilities and pattern identification can mitigate this.

Missing Character: The model struggles with recognizing underlying alphabetical or numerical patterns and sometimes makes calculation errors after identifying the pattern. Strengthening both sequence recognition and calculation accuracy is important.

Non-Verbal Analogy: Visual analogy problems reveal difficulties in identifying figure transformations such as rotations or reflections. The model would benefit from improved spatial reasoning and visual transformation handling.

Non-Verbal Odd One Out: The model frequently misidentifies the attribute that sets the odd figure apart in a visual set. Enhancing its ability to classify subtle visual differences can improve performance.

Number and Ranking: Errors in determining sequences or ranks in numerical problems arise from miscalculations. A stronger grasp of ranking principles and numerical reasoning is essential for more accurate outcomes.

Paper Folding & Cutting: The model has difficulty predicting the results of folds and cuts, often misinterpreting how patterns will replicate upon unfolding.

Puzzle Test: Incorrect interpretation of puzzle clues or failure to apply logical deduction correctly are common errors. The model also struggles with numerical-based puzzle elements, suggesting a need for more systematic problem-solving approaches.

Series: The model often fails to recognize numerical or alphabetical progression patterns and makes calculation errors after identifying a pattern. Improved pattern detection and calculation accuracy would enhance performance.

Statement & Conclusions: Misapplications of logical deduction, particularly in determining whether a conclusion follows from a given statement, are frequent errors. Reinforcing critical thinking skills and logical structure comprehension will help address these issues.

Syllogisms: The model struggles with applying syllogistic rules correctly and often misinterprets categorical relationships. A stronger understanding of syllogistic reasoning and relational logic is necessary.

Time and Clock: Miscalculations related to time intervals or angles, particularly involving exceptions, often lead to errors. Enhancing the model's mathematical reasoning around time and angles will improve performance in these questions.

Venn Diagrams: Common errors include misrepresentation of set relationships and logical errors in diagram interpretation. Enhancing understanding of set theory and logical interpretation will help reduce errors.

Mathematical Operations: The model often misapplies sign changes or substitutions, and errors occur when performing calculations after applying these changes. Focusing on improving accuracy in mathematical operations and sign transformations is necessary.

Mirror, Water, & Images: Incorrect application of reflection principles leads to selection errors, and the model struggles with predicting figure changes under reflection. Strengthening spatial visualization and understanding reflection principles will improve outcomes.

Non-Verbal Series: The model often misinterprets the progression of visual figure transformations, leading to incorrect sequence predictions. Enhancing pattern recognition and spatial reasoning for visual sequences is needed.

Dot Problem: The model fails to correctly identify overlapping regions for dot placement and struggles with understanding the spatial relationships between shapes. Better understanding of in-

tersections and spatial overlap is crucial.

A.3 Additional Results

A.3.1 Preliminary Human Evaluation

Two human annotators were tasked with solving 10 questions for each category for both textual and multi-modality questions types. Results are shown in Table 6 and 7. Average accuracy for textual category is close to 85%, and for multi-modal category is around 83.33%.

A.3.2 Option Shuffling Experiment Results

Results for textual questions for Gemini 1.5 Pro and GPT-4o are shown in Tables 8 and 10. Results for multi-modal questions for Gemini 1.5 Pro and GPT-4o are shown in Tables 11 and 9.

Additional Analysis of Option Shuffling Experiment : The performance of random set is close to the original set for GPT-4o, but has a significant difference(4-6 percent) for Gemini 1.5 Pro model, for both textual and multimodel questions. This result suggests that Gemini1.5 Pro may be more prone to memorizing results compared to GPT-4o, as it shows greater sensitivity to the position of the options.

A.4 Model Details Hyper parameters

We use the following models for running experiments:

LLMs: GPT-3.5-Turbo, Llama3-70b (AI@Meta, 2024), Mixtral8x7b (Jiang et al., 2024a) using the Standard QA strategy with both zero shot COT and few shot COT.

Open-Source VLMs[7]: QWEN-VL-chat-7b (Bai et al., 2023), CogVLM-2-Llama3-chat-19B (Wang et al., 2023a), internlm-xcomposer2-vl-7b (Dong et al., 2024),Ovis1.6-Gemma2-9B(Lu et al., 2024),LLaVA-OneVision-Qwen2-72b-ov-chat (Li et al., 2024) using the Standard VQA and Image-Only strategies with zero shot COT. [8]

Proprietary VLMs: Gemini-1.5-Pro (Reid et al., 2024), Gemini-1.5-Flash and GPT-4o are the proprietary models used.We provide the prompts and hyperparameters in the Appendix A.5 and A.4. We have also evaluated the cheaper and faster version of Gemini, namely Gemini-1.5-Flash, which has shown comparable performance to Gemini-1.5-Pro.

[7]Evaluated on A6000 machine

[8]Refer to technical discussion section for details on why few shot COT is challenging with open source models.

Default hyperparameters from the Hugging Face model were used. List along with modifications(if any) are listed below

- **GPT-4o.** Temparature = 0.0, Output_format = json
- **GPT-3.5.** Temparature = 0.0, Output_format = json
- **Gemini-1.5-Pro.** Temparature = 1.0
- **Qwen-vl-chat.** seed = 1234, precision = float16(half)
- **Cogagent2-Llama3-8b.** precision=bf16
- **InterLM-XComposer.** precision=half
- **LLaVA-OneVision-Qwen2-72b-ov-chat**
- **Ovis1.6-Gemma2-9B**

A.5 Prompt Templates

System prompts for different modelling strategies, i.e., ***Standard QA, Image only, Interleaved and Standard VQA***, are shown in Figure 3.

We present the prompt templates used across different modeling and prompting strategies for GPT-4o. We apply the same prompt template consistently for each model within the same strategy.

A.5.1 Interleaving

Zero shot

Listing 1: Prompt template for GPT-4o zero shot with interleaving. The template includes placeholders (‘...‘) for question direction, question text, answer choices, and their corresponding images, which are encoded in base64 format. All the images are optional and can be there or not based on the question.

```
{
  "role": "system",
  "content": "You are a brilliant
      problem solver... Please select
      the correct answer choice."
},
{
  "role": "user",
  "content": [
    {"type": "text", "text": "
        questionDirection: ..."},
    {"type": "image_url", "image_url":
        {"url": "data:image/png;base64
        ,..."}},
    {"type": "text", "text": "\
        nquestionText: ..."},
    {"type": "image_url", "image_url":
        {"url": "data:image/png;base64
        ,..."}},
```

Annotator	SER	ALP	ODO	ANA	COD	NUM	BLR	MTO	PUZ	SYL	STC	DAT	Aggregate
First	90	90	80	100	90	90	80	90	100	80	100	80	89.17
Second	80	90	90	80	80	80	90	100	90	60	80	70	82.50
Third	80	80	90	90	90	90	80	90	90	70	80	70	83.33

Table 6: **Human Evaluation of Textual Questions.** Percentage accuracy for 3 human annotators.

Annotator	DIR	VEN	TIM	MIS	NVS	NVO	NVA	INC	MIR	CUB	PAP	EMB	FIG	DOT	Aggregate
First	100	100	60	80	80	60	90	100	80	90	90	100	70	100	85.71
Second	90	70	50	100	100	50	100	90	70	90	70	90	90	60	80.71
Third	80	90	70	100	70	50	70	90	100	80	80	100	90	100	83.57

Table 7: **Human Evaluation of Multi-modal Questions.** Percentage accuracy for 2 human annotators.

Ans Option	SER	ALP	ODO	ANA	COD	NUM	BLR	MTO	PUZ	SYL	STC	DAT	Aggregate
First	59.90	21.99	53.92	62.69	41.61	60.19	59.26	37.37	70.18	50.00	67.95	49.26	52.86
Second	65.75	26.24	60.59	69.09	46.76	66.67	67.72	43.09	71.23	63.64	66.02	46.67	57.79
Third	61.72	56.03	62.94	73.07	51.68	71.46	67.46	42.08	70.18	53.03	69.87	56.30	61.32
Fourth	62.24	28.02	58.82	67.55	48.77	72.18	68.78	51.85	71.93	47.73	70.83	49.26	58.16
Random	62.11	25.18	57.26	68.87	53.02	62.83	68.25	47.81	74.03	47.73	69.23	45.19	56.79
Original	63.67	39.36	60.00	69.54	61.07	68.35	58.73	45.45	81.05	65.91	70.19	63.33	62.22

Table 8: **Gemini 1.5 Pro Option Shuffling Results on Text Questions.** *Original,* is the option arrangement same as in the original question paper. *Random,* is random position of the correct option.*First, Second, Third, Fourth* are the position of correct answers.

Ans Option	DIR	VEN	TIM	MIS	NVS	NVO	NVA	INC	MIR	CUB	PAP	EMB	FIG	DOT	Aggregate
First	57.29	50.75	56.86	34.91	50.88	34.29	40.00	54.26	52.90	42.32	28.82	22.92	45.54	33.33	43.22
Second	52.43	63.96	64.71	34.12	31.23	23.81	41.33	26.24	27.54	38.58	37.85	31.60	32.39	23.19	37.78
Third	67.36	63.06	68.63	48.55	20.00	20.48	22.00	24.82	22.46	40.45	21.88	27.08	40.38	40.58	37.70
Fourth	59.03	59.46	63.40	35.70	9.12	11.43	18.00	15.25	32.97	48.69	27.78	24.30	44.60	10.15	32.85
Random	62.15	58.86	58.82	33.86	22.46	23.33	34.00	30.50	29.35	46.07	34.38	26.39	38.50	27.54	37.59
Original	63.54	64.86	70.59	37.01	33.68	25.71	32	38.3	35.87	43.82	30.21	36.46	46.48	30.43	42.06

Table 9: **Gemini 1.5 Pro Option Shuffling Results on Multi-modal Questions.** *Original,* is the option arrangement same as in the original question paper. *Random,* is random position of the correct option. *First, Second, Third, Fourth* are the position of correct answers.

Ans Option	SER	ALP	ODO	ANA	COD	NUM	BLR	MTO	PUZ	SYL	STC	DAT	Aggregate
First	52.34	29.79	47.45	64.46	50.34	44.60	65.08	36.70	64.56	57.58	70.19	51.48	52.88
Second	45.96	37.94	64.12	60.93	47.88	46.28	66.40	38.72	65.62	62.12	73.72	51.11	55.07
Third	42.32	38.65	63.33	60.26	42.73	44.36	64.55	38.04	66.67	57.58	72.44	48.15	53.26
Fourth	34.38	39.00	59.41	56.07	35.57	39.81	60.84	40.40	67.72	65.15	75.00	55.93	52.44
Random	44.53	35.46	56.67	61.15	46.09	41.25	64.02	35.69	66.67	60.61	75.00	48.15	52.94
Original	42.58	35.11	55.88	65.56	38.26	42.45	68.25	41.41	69.47	63.64	70.19	43.33	53.01

Table 10: **GPT-4o Option Shuffling Results on Textual Questions.** *Original,* is the option arrangement same as in the original question paper. *Random,* is random position of the correct option. *First, Second, Third, Fourth* are the position of correct answers.

```
    {"type": "text", "text": "\
        nanswerChoices: \n 1. ... \n 2.
        ... \noptionImages: \n..."},
    {"type": "text", "text": "Answer in
        the json format as follows: \n
        {'answer': <
        correct_option_number>, '
        explanation': <explanation>}"}
]
```

```
}
```

Few shot

Ans Option	DIR	VEN	TIM	MIS	NVS	NVO	NVA	INC	MIR	CUB	PAP	EMB	FIG	DOT	Aggregate
First	44.10	61.56	31.37	29.13	23.86	32.86	24.67	12.41	30.07	41.20	31.25	21.88	52.11	8.70	31.80
Second	42.36	54.65	43.79	32.28	22.11	29.05	31.00	29.08	40.94	49.81	42.01	26.04	46.48	30.43	37.15
Third	50.00	54.95	39.87	31.23	20.70	25.24	30.33	27.31	34.42	40.08	37.85	30.91	50.24	31.88	36.07
Fourth	51.73	48.35	37.25	26.25	23.86	18.57	30.67	30.14	27.17	37.45	38.54	25.35	41.31	36.23	33.78
Random	44.79	54.35	37.25	29.66	22.11	23.81	24.67	25.53	32.61	38.21	35.07	30.21	39.44	23.19	32.92
Original	37.5	50.45	41.18	29.92	16.84	22.86	26	23.4	34.78	35.96	27.08	22.92	45.07	17.39	30.81

Table 11: **GPT-4o Option Shuffling Results on Multi-modal Questions.** *Original,* is the option arrangement same as in the original question paper. *Random,* is random position of the correct option. *First, Second, Third, Fourth* are the position of correct answers.

Ans Option	SER	ALP	ODO	ANA	COD	NUM	BLR	MTO	PUZ	SYL	STC	DAT	Aggregate
First	80.63	88.15	77.65	71.78	84.09	85.51	83.33	84.69	87.80	81.08	74.04	80.95	80.88
Second	76.68	84.78	78.82	76.55	85.23	86.23	84.92	82.65	84.15	78.38	71.15	82.14	80.45
Third	83.00	84.78	83.53	79.31	86.36	83.33	84.13	79.59	86.59	78.38	75.96	82.14	82.43
Fourth	81.42	85.87	78.82	77.93	86.36	86.96	83.33	82.65	89.02	75.68	79.81	80.95	82.29

Table 12: **O1-preview Option Shuffling Results on Textual Questions.** *First, Second, Third, Fourth* are the position of correct answers.

Listing 2: Few-shot CoT prompt template for GPT-4o. The template includes placeholders for multiple solved examples (with directions, questions, images, answer choices, correct answers, and explanations) followed by a new unsolved question (with directions, questions, images, and answer choices). GPT-4o is expected to provide a structured answer in JSON format. All the images are optional and can be there or not based on the question.

```
{
  "role": "system",
  "content": "Understand the following
      problems carefully... then answer
      the new question given at the end
      ."
},
{
  "role": "user",
  "content": [
    {"type": "text", "text": "example
        1:"},
    {"type": "text", "text": "
        questionDirection: ... direction
         image"},
    {"type": "image_url", "image_url":
        {"url": "data:image/png;base64
        ,..."}},
    {"type": "text", "text": "\
        nquestionText: ... question
        image"},
    {"type": "image_url", "image_url":
        {"url": "data:image/png;base64
        ,..."}},
    {"type": "text", "text": "\
        nanswerChoices: \n 1. ... \n 2.
        ... \noptionImages: \n..."},
    {"type": "text", "text": "{'answer':
         <correct_option_number>, '
        explanation': ...}"},
    {"type": "text", "text": "So the
        solution is ... solution image
        "},
    {"type": "image_url", "image_url":
        {"url": "data:image/png;base64
        ,..."}},
    {"type": "text", "text": "\n\n..."},
    {"type": "text", "text": "example
        2:"},
    ...
    {"type": "text", "text": "example
        3:"},
    ...
    {"type": "text", "text": "\n\n..."},
    {"type": "text", "text": "now solve
        this question..."}
    {"type": "text", "text": "
        questionDirection: ..."},
    {"type": "image_url", "image_url":
        {"url": "data:image/png;base64
        ,..."}},
    {"type": "text", "text": "\
        nquestionText: ..."},
    {"type": "image_url", "image_url":
        {"url": "data:image/png;base64
        ,..."}},
    {"type": "text", "text": "\
        nanswerChoices: \n 1. ... \n 2.
        ... \noptionImages: \n..."},
    {"type": "text", "text": "Answer in
        the json format as follows: \n
        {'answer': <
        correct_option_number>, '
        explanation': <explanation>}"}
  ]
}
```

A.5.2 Image Only

Zero shot

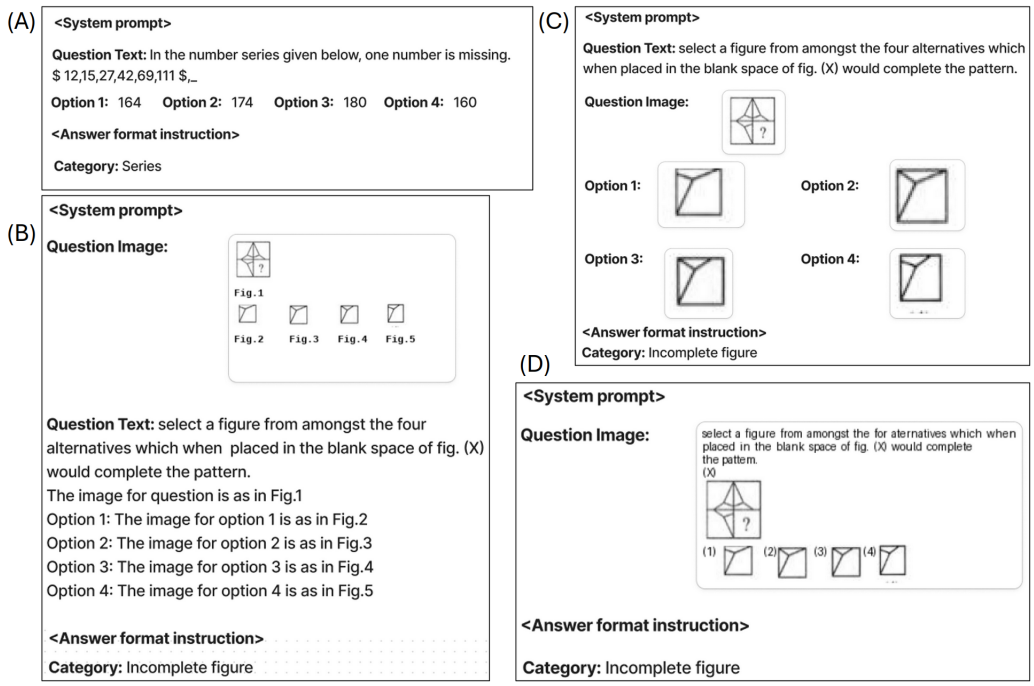


Figure 3: **Examples Showing Input to Different Proposed modelling strategies**.(A) Text Only Standard QA strategy(B) Standard VQA (C) Interleaved Strategy (D) Image Only.

Listing 3: Zero-shot prompt template for image-only question answering. The prompt includes a system instruction to solve the problem and provide the answer in JSON format, followed by the input image encoded in base64.

```
{
  "role": "system",
  "content": "You are a brilliant
      problem solver... answer the
      correct option from the given
      choices along with a explanation.
      Answer in form of json in this
      format: {'answer': <
      correct_option_number>, '
      explanation': <explanation>}"
},
{
  "role": "user",
  "content": [
    {"type": "image_url", "image_url":
        {"url": "data:image/png;base64
        ,..."}},
  ]
}
```

Few shot

Listing 4: Few-shot prompt template for image-only question answering. The template demonstrates two examples, each with a question image, the correct answer, an explanation, and potentially solution images. It then presents a new question image and asks for a structured answer in JSON format.

```
{
  "role": "system",
  "content": "Understand the following
      problems carefully ..."
},
{
  "role": "user",
  "content": [
    {"type": "text", "text": "You are a
        brilliant problem solver...
        Please select the correct answer
         choice."},
    {"type": "text", "text": "example
        1:"},
    {"type": "image_url", "image_url":
        {"url": "data:image/png;base64
        ,..."}},
    {"type": "text", "text": "\n so the
        solution to this example is as
        follows\n{'answer': <
        correct_option_number>, '
        explanation': ...}"},
    {"type": "image_url", "image_url":
        {"url": "data:image/png;base64
        ,..."}},
    {"type": "text", "text": "\n\n..."},
    {"type": "text", "text": "example
        2:"},
    ...
    {"type": "text", "text": "example
        3:"},
    ...
    {"type": "text", "text": "\n\n\n now
         answer the following question
        "},
    {"type": "image_url", "image_url":
        {"url": "data:image/png;base64
        ,..."}},
  ]
}
```

A.5.3 Standard VQA

Zero Shot

Listing 5: Zero-shot prompt template for Standard VQA on GPT-4o. The template instructs the model to solve a multiple-choice question with reference to an image. The expected output is a JSON object with the correct answer number and a corresponding explanation.

```
{
  "role": "system",
  "content": "You are a brilliant
      problem solver. Solve the given
      multiple choice question. Answer
      in the json format as follows: \n
      {'answer': <correct_option_number
      >, 'explanation': <explanation>}"
},
{
  "role": "user",
  "content": [
    {"type": "text", "text": "refer to
        this image for references in
        question: \n"},
    {"type": "image_url", "image_url":
        {"url": "data:image/png;base64
        ,..."}},
    {"type": "text", "text": "\nquestion
        : ... \n answer the question
        with the correct option number
        and explanation in the json
        format as follows: \n {'answer':
         <correct_option_number>, '
        explanation': <explanation>}"}
  ]
}
```

Few shot

Listing 6: Few-shot prompt template for Standard VQA on GPT-4o. The template showcases a few-shot example with question, images, answers, explanations, and optional solution images, followed by a new question for the model to answer in JSON format.

```
[
    {"type": "system", "content": "You
        are a brilliant problem solver
        ... First understand the
        provided questions and then
        answer the new question given at
         the end."},
    {"type": "user", "content": [
        {"type": "text", "text": "
            example 1:"},
        {"type": "text", "text": "refer
            to this image for references
             in question: \n"},
        {"type": "image_url", "image_url
            ": {"url": "data:image/png;
            base64,..."}},
        {"type": "text", "text": "\
            nquestion: ... \n answer the
             question with the correct
            option number and
            explanation in the json
            format as follows: \n {'
            answer': <
            correct_option_number>, '
            explanation': <explanation
            >}"},
        {"type": "text", "text": "so the
             answer to this question is
            as follows: \n {'answer': <
            correct_option_number>, '
            explanation': ...}"},
        {"type": "text", "text": "refer
            to this image for solution:
            \n"},
        {"type": "image_url", "image_url
            ": {"url": "data:image/png;
            base64,..."}},
        {"type": "text", "text": "\n
            ..."},
        {"type": "text", "text": "\n now
             as you have got the idea of
             the questions, let's answer
             the following question with
             a thorough explanation: \n
            "},
        {"type": "text", "text": "refer
            to this image for references
             in question: \n"},
        {"type": "image_url", "image_url
            ": {"url": "data:image/png;
            base64,..."}},
        {"type": "text", "text": "\
            nquestion: ... \n answer the
             question with the correct
            option number and
            explanation in the json
            format as follows: \n {'
            answer': <
            correct_option_number>, '
            explanation': <explanation
            >"}
    ]}
]
```

B Examples of the dataset

1. Series Problem

Here we need to find missing element in number, alphabet or alpha-numeric series

Question: Find the missing element in the following series:

$$4, 6, 6, 15, 8, 28, 10, \_\_\_\_\_$$

1. 36
2. 39
3. 45
4. 38

Answer: 3

Explanation: First series: $4, 6, 8, 10$
Second series : $6, 15, 28, ?$
Differences in the second series are 9, 13, 17 etc.
Hence the next term is $28 + 17 = 45$.

2. Alphabet Test
This question involves operations on the English alphabet:
Question: Which letter should be the ninth letter to the left of the ninth letter from the right, if the first half of the given alphabet is reversed?

$$A\ B\ C\ D\ E\ F\ G\ H\ I\ J\ K\ L\ M$$

$$N\ O\ P\ Q\ R\ S\ T\ U\ V\ W\ X\ Y\ Z$$

1. 1, 2, 3, 4, 5
2. 1, 5, 3, 4, 2
3. 5, 1, 2, 3, 4
4. 3, 1, 5, 2, 4

Answer: 2
Explanation: The new alphabet series is M LK J I H G F E D C B A N O P Q R S T U V W X Y Z. The 9th letter from right is R and the ninth letter to the left of R is E.

3. Classification/Odd One Out
This category of questions requires identifying the option that doesn't belong with the others.
Question: Find the odd term/wrong term or which is different from the rest three terms.

1. 31:96
2. 15:63
3. 22:91
4. 23:95

Answer: 1
Explanation: The pattern is: first number ×4+3= second number.

$$22 \times 4 + 3 = 91$$
$$15 \times 4 + 3 = 63$$
$$23 \times 4 + 3 = 95$$
$$31 \times 4 + 3 = 127$$

The first option (31:96) does not follow this pattern.

4. Analogy Problems
This category of questions presents an analogy where the first two terms have a relationship. You need to identify the pair that shares the same relationship.
Question: Square : Cube ::

1. Rectangle : Cuboid
2. Triangle : Square
3. Quadrilateral : Cuboid
4. Cuboid : Rectangle

Answer: 1
Explanation: A cube is the three-dimensional extension of a square. Similarly, a cuboid is the three-dimensional extension of a rectangle.

5. Coding-Decoding
In this category, an example of a code is given. You need to infer the rule and then code/decode a new example.
Question: If A = 2, T = 40, and ACT = 48, then TAKE = ?

1. 68
2. 58
3. 74
4. 76

Answer: 3
Explanation:
The rule is: (Position value of the letter in the alphabet) ×2 = Code

$$A = 1 \times 2 = 2$$
$$T = 20 \times 2 = 40$$
$$ACT = (1 + 3 + 20) \times 2 = 48$$
$$TAKE = (20 + 1 + 11 + 5) \times 2 = 74$$

6. Number and Ranking Problems
This category of questions involves arranging items in a logical sequence.
Question: Arrange the following words in a meaningful sequence.
1. Key, 2. Door, 3. Lock, 4. Room, 5. Switch on

1. 5, 1, 2, 4, 3
2. 4, 2, 1, 5, 3

3. 1, 3, 2, 4, 5

4. 1, 2, 3, 5, 4

Answer: 3
Explanation: The logical order of actions is: You need the Key (1) To open the Lock (3) On the Door (2) To enter the Room (4) And then Switch on (5) the lights.

7. Blood Relation
This category involves decoding relationships based on given symbols and then analyzing statements to determine their accuracy.
Question: Which of the following is correct?
Symbols and their meanings:
* $P = Q$: Q is the father of P * $P * Q$: P is the sister of Q * $P ? Q$: Q is the mother of P * $P\ Q$: P is the brother of Q * $P \subset Q$: Q is the son of P * $P \times Q$: P is the daughter of Q

1. $V \times T * P$ means P is the maternal uncle of V.

2. $D ? V \times T$ means D is the granddaughter of T.

3. $L \subset M\ R$ means R is the paternal uncle of L.

4. $M\ R * R\ D ? V$ means M is the son of V.

Answer: 4
Explanation:
Let's break down each statement:
1. $V \times T * P$: * $V \times T$: V is the daughter of T * $T * P$: T is the sister of P * Conclusion: P could be the maternal uncle *or* maternal aunt of V. So, this statement is incorrect.
2. $D ? V \times T$: * $D ? V$: V is the mother of D * $V \times T$: V is the daughter of T * Conclusion: D could be the grandson *or* granddaughter of T. So this statement is incorrect
3. $L \subset M\ R$: * $L \subset M$: M is the son of L * $M\ R$: M is the brother of R * Conclusion: R is the son of L. So, R is the paternal uncle of M, not L. This statement is incorrect
4. $M\ R * R\ D ? V$: * $M\ R$: M is the brother of R * $R * D$: R is the sister of D * $D ? V$: V is the mother of D * Conclusion: M is the brother of R, who is the daughter of V. This means M is the son of V. This statement is correct.
Therefore, the correct statement is option 4.

8. Mathematical Operations
This category involves deducing the underlying mathematical operation from given examples and applying it to a new problem.
Question: If $37 + 42 = 16$, $43 + 54 = 16$, and $25 + 34 = 14$, then $65 + 35 =$?

1. 100

2. 91

3. 18

4. 19

Answer: 4
Explanation:
The operation is to sum the individual digits of the numbers being 'added'.

$$37 + 42 \rightarrow 3 + 7 + 4 + 2 = 16$$
$$43 + 54 \rightarrow 4 + 3 + 5 + 4 = 16$$
$$25 + 34 \rightarrow 2 + 5 + 3 + 4 = 14$$
$$65 + 35 \Rightarrow 6 + 5 + 3 + 5 = 19$$

9. Direction Sense
This category involves understanding directions and calculating distances based on movements.
Question: A man walks 1 km towards East and then he turns to South and walks 5 km. Again he turns to East and walks 2 km, after this he turns to North and walks 9 km. Now, how far is he from his starting point?

1. 3 km

2. 4 km

3. 5 km

4. 7 km

Answer: 3
Explanation:
* A: Starting point
* B: 1 km East of A
* C: 5 km South of B
* D: 2 km East of C
* E: 9 km North of D
We want to find the distance AE.
* DF = BC = 5 km
* EF = (DE - DF) = (9 - 5) km = 4 km
* BF = CD = 2 km
* AF = AB + BF = 1 + 2 = 3 km Using the Pythagorean theorem on triangle AEF:

$$AE = \sqrt{AF^2 + EF^2}$$
$$= \sqrt{3^2 + 4^2} = \sqrt{25} = 5 \text{ km}$$

Therefore, the man is 5 km from his starting point.

10. Venn Diagrams

This category involves interpreting information represented in Venn diagrams.

Directions: In the following diagram, three classes of population are represented by three figures. The triangle represents school teachers. The square represents married persons. The circle represents persons living in joint families.

Question: School teachers who are married but do not live in joint families are represented by

Question Image

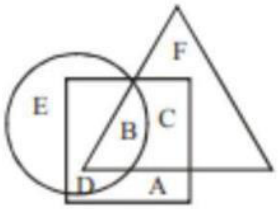


Figure 4: Venn Diagram Problem: Question 10

1. C
2. F
3. A
4. D

Answer: 1

Explanation:

Married teachers are represented by the intersection of the triangle (teachers) and the square (married), which includes regions B and C. We need those who do not live in joint families, so we exclude the circle. Only region C satisfies both conditions: married teachers outside the joint family circle. Therefore, the answer is C.

11. Time and Clock

This category involves calculations related to days, dates, and calendars.

Question: If it was Saturday on 17th December, 2002, what was the day on 22nd December, 2004?

1. Monday
2. Tuesday
3. Wednesday
4. Sunday

Answer: 4

Explanation:

The period from 17th Dec. 2002 to 16th Dec. 2003 is 365 days (52 weeks + 1 day).
So, 16th Dec. 2003 is also a Saturday.
The period from 16th Dec. 2003 to 15th Dec. 2004 is 366 days (2004 is a leap year).
So, 15th Dec. 2004 is also a Saturday.
Counting forward, 22nd Dec. 2004 is a Sunday.
Therefore, the answer is Sunday.

12. Missing Character

This category involves predicting a missing element within a figure, often requiring spatial reasoning.

Question: Find the missing term in the following figure:

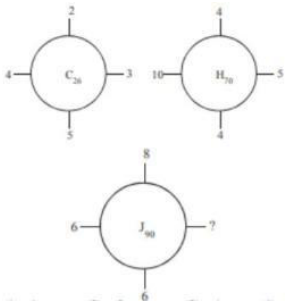


Figure 5: Missing Character Problem: Question 12

1. 1
2. 2
3. 4
4. 10

Answer: 3

Explanation:

The number inside the circle is obtained by the following rule:
* Sum the upper number, the lower number, and the alphabetical position of the letter. * Multiply this sum by the number on the right. * Subtract the number on the left from the product.
Applying this rule to the given examples:
* $(2 + C + 5) \times 3 - 4 = (2 + 3 + 5) \times 3 - 4 = 26$ *
$(4 + H + 4) \times 5 - 10 = (4 + 8 + 4) \times 5 - 10 = 70$
Let the missing number be 'x'. Then,
* $(8 + J + 6) \times x - 6 = 90$ *
$(8 + 10 + 6) \times x = 96$ * $x = 4$
Therefore, the missing number is 4.

13. Non-Verbal Reasoning - Series Continuation
Directions: Each question consists of five problem figures (A, B, C, D, and E) followed by four answer figures (1, 2, 3, and 4). Select the figure that continues the series established by the problem figures.
Problem Figures:

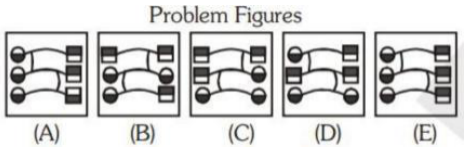


Figure 6: Non-Verbal Reasoning -Series Continuation: Question 13

1. 

2. 

3. 

4. 

Answer: 1
Explanation: The following figures explain the pattern.

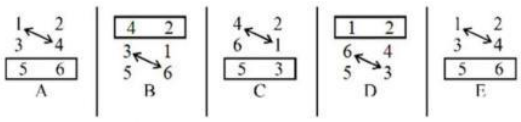


Figure 7: Problem 13 Solution Explanation.

14. Non-Verbal Classification/Odd One Out
Questions: Which is the odd one out ?

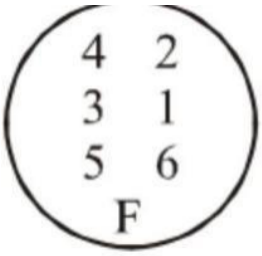


Figure 8: Problem 13 Solution.

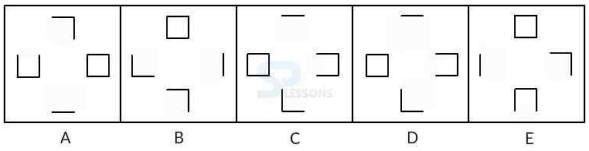


Figure 9: Problem 14

Answer: B
Explanation: Each one of the figures except figure B, contains - one complete square, one cup-shaped element having three sides, one 'L'-shaped element having two sides and one straight line. Therefore, the figure B is different from the rest.

15. Non-Verbal Reasoning - Analogy
Directions: Each question consists of two sets of figures: A, B, C, and D. A definite relationship exists between figures A and B. Establish a similar relationship between figures C and D by choosing a suitable figure D from the answer set.

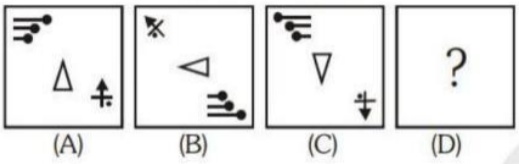
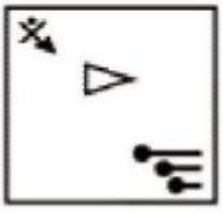
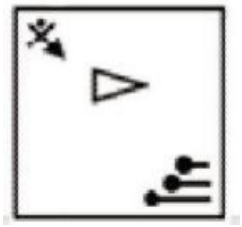


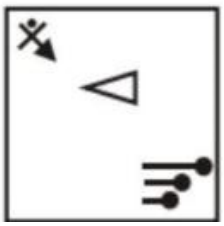
Figure 10: Problem Non-Verbal Reasoning - Analogy.

Answer Figures:

1. 

2. 

3. 

4. 

Answer: 3
Explanation: By observation.

16. Incomplete Figure
This category involves identifying the missing part of a figure to complete it.
Question: Which of the answer figures will complete the matrix figure?
Question Figure:

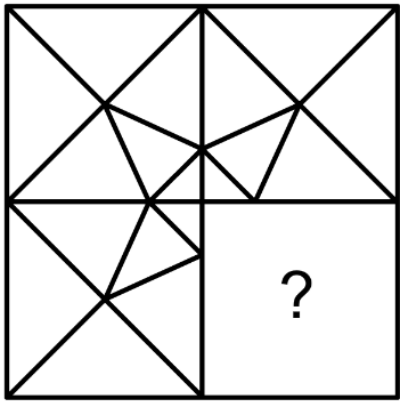


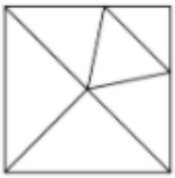
Figure 11: Question 16 Problem

Answer Figures:

1. 

2. 

3. 

4. 

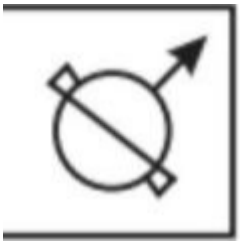
Answer: 1
Explanation: By observation.

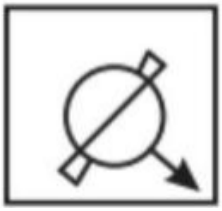
17. Mirror Image
This category involves identifying the mirror image of a given figure.
Question: The mirror image of the given diagram is:
Question Figure:

Figure 12: 17.1

Answer Figures:

1. 

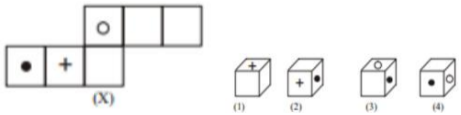
2. 

3. 

4. 

Answer: 2
Explanation: By observation.

18. Cube and Dice
This category involves visualizing the folding of a 2D net into a 3D cube and identifying possible resulting cubes.
Question: Select from the alternatives, the box(es) that can be formed by folding the sheet shown in the figure.
Question Figure:

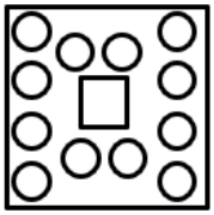
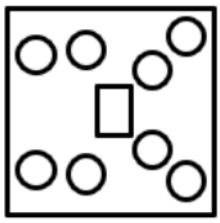
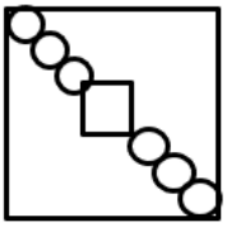
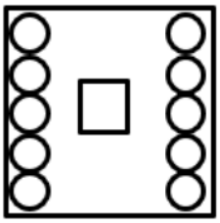


1. 1 only
2. 1, 2, and 3 only
3. 2 and 3 only
4. 1, 2, 3, and 4

Answer: 4
Explanation:
When the sheet is folded to form a cube:
* The face with a dot will be opposite a blank face.
* The face with a "+" sign will be opposite another blank face * The face with a circle will be opposite the third blank face
Considering these relationships, all four cubes shown in the options (1, 2, 3, and 4) can be formed.

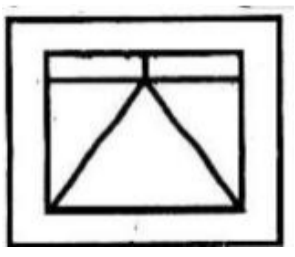
19. Paper Folding and Cutting
Directions: In the following questions, a square sheet of paper is folded along the dotted lines, and then cuts are made on it. Select the figure from the given choices that shows how the sheet would look when opened.

Choose the correct figure.

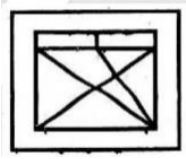
1. 
2. 
3. 
4. 

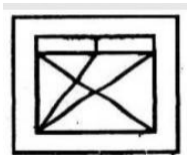
Answer: 1
Explanation: By observation.

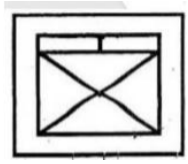
20. Embedded Figure
Directions: In the following question, there is a question figure, which is embedded in one of the answer figures. Trace out the correct figure.
Question Figure:

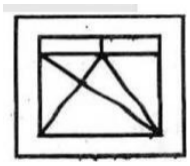


Answer Figures:

1. 

2. 

3. 

4. 

Answer: 4

21. Puzzle Test

This category involves solving general puzzles based on provided information.
Directions: Read the following information carefully and answer the question that follows:

(i) There is a group of five persons: A, B, C, D, and E.

(ii) One of them is a Teacher, one is a Doctor, one is a Journalist, one is an Industrialist, and one is an Advocate.

(iii) Three of them - A, C, and the Advocate - prefer tea to coffee.

(iv) Two of them - B and the Journalist - prefer coffee to tea.

(v) The Industrialist, D, and A are friends, but two of these prefer coffee to tea.

(vi) The Teacher is C's brother.

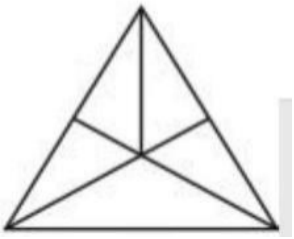
Question: Who is the Teacher?

1. B
2. A
3. C
4. D

Answer: 2
Explanation:
From the given information, we can deduce:
* A (Teacher), C (Doctor), E (Advocate) prefer tea to coffee. * B (Industrialist), D (Journalist) prefer coffee to tea.

22. Figure Partition

This category involves counting specific shapes or components within a given figure.
Question: The number of triangles in the following figure is:

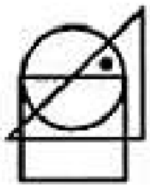


1. 9
2. 10
3. 11
4. 12

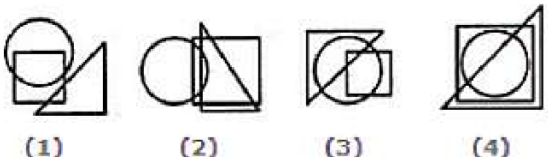
Answer: 4
Explanation:
By careful observation of the figure, we can count a total of 12 triangles.

23. Dot Problem

Directions: Select the alternative which satisfies the same conditions of placement of dots as shown in the figure.
Question Figure:



Answer Figures:



Answer: 3
Explanation: In figure (X), the dot is placed in the region which is common to the circle and triangle. Now, we have to search similar common region in the four options. Only in figure (3), we find such a region which is common to the circle and triangle.

24. Syllogisms
This category involves evaluating logical arguments and identifying valid conclusions based on given statements.
Directions: Each question consists of five or six statements followed by options containing three statements in a specific order. Choose the option which indicates a valid argument, where the third statement is a conclusion drawn from the preceding two statements.
Statements:

A. All synopses are poets.

B. Some synopses are mentors.

C. Some X are not mentors.

D. All X are poets.

E. All synopses are mentors

F. All synopses are X.

Options:

1. ABC
2. AEC
3. FEC
4. DFA

Answer: 4
Explanation:
Let's analyze each option:

1. **ABC**: Irrelevant
2. **AEC**: Irrelevant
3. **FEC**: The conclusion may or may not be true.
4. **DFA**: * D: All X are poets * F: All synopses are X * Conclusion: All synopses are poets. This is a valid conclusion as it follows from the first two statements

Thus, the correct answer is option 4.

25. Statement & Conclusions
This category involves making inferences based on given statements.
Directions: In the question below, two statements are given followed by two conclusions (I and II). Take the statements to be true and then decide which of the conclusions logically follows.
Statements: The average number of students per teacher is 50 in the urban area, whereas it is 60 in rural areas. The national average is 55.
Conclusions:

I. The student-teacher ratio in the rural areas is higher than in the urban areas.

II. More students study with the same teacher in the rural areas as compared to those in the urban areas.

Options:

1. if conclusion I follows
2. if conclusion II follows
3. if either conclusion I or II is implicit
4. if neither conclusion I nor II follows

Answer: 2
Explanation:
* Without absolute figures (total number of students and teachers), we cannot conclude anything about the student-teacher ratio (Conclusion I).
* The average number of students per teacher is higher in rural areas (60) compared to urban areas (50). This directly implies that more students study with the same teacher in rural areas (Conclusion II).
Therefore, only conclusion II follows.

26. Data Sufficiency
This category involves determining whether given statements provide enough information to answer a question.
Directions: Each question has a problem and two statements (I and II). Decide if the information in the statements is sufficient for answering the problem.
Question: Who is the father of M?
Statements:

I. A and B are brothers.

II. B's wife is the sister of M's wife.

Options:

1. if the data in statement I alone are sufficient to answer the question
2. if the data in statement II alone are sufficient to answer the question

3. if the data either in I or II alone are sufficient to answer the question
4. if the data even in both the statements together are not sufficient to answer the question
5. if the data in both the statements together are needed

Answer: 4
Explanation:
* From statement II, we conclude that B is the brother-in-law of M. * Even combining both statements, we cannot determine who the father of M is.
Therefore, the data in both statements together are not sufficient to answer the question.