EEE-BENCH: A COMPREHENSIVE MULTIMODAL ELECTRI-CAL AND ELECTRONICS ENGINEERING BENCHMARK

Anonymous authors

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ABSTRACT

Recent studies on large language models (LLMs) and large multimodal models (LMMs) have demonstrated promising skills in various domains including science and mathematics. However, their capability in more challenging and real-world related scenarios like engineering has not been systematically studied. To bridge this gap, we propose EEE-Bench, a multimodal benchmark aimed at assessing LMMs' capabilities in solving practical engineering tasks, using electrical and electronics engineering (EEE) as the testbed. Our benchmark consists of **2860** hand-picked and carefully curated multiple-choice and free-form problems spanning **10** essential subdomains such as analog circuits, control systems, etc. Compared to benchmarks in other domains, engineering problems are intrinsically 1) more visually complex and versatile and 2) less deterministic in solutions. Successful solutions to these problems often demand more-than-usual rigorous integration of visual and textual information as models need to understand intricate images like abstract circuits and system diagrams while taking professional instructions, making them excellent candidates for LMM evaluations. Alongside EEE-Bench, we provide extensive quantitative evaluations and fine-grained analysis of 17 widely-used open and closed-sourced LLMs and LMMs. Our results demonstrate notable deficiencies of current foundation models in EEE, with an average performance ranging from 19.48% to 46.78%. Finally, we reveal and explore a critical shortcoming in LMMs which we term "laziness": the tendency to take shortcuts by relying on the text while overlooking the visual context. In summary, we believe EEE-Bench not only reveals some noteworthy limitations of LMMs but also provides a valuable resource for advancing research on their application in practical engineering tasks, driving future improvements in their capability to handle complex, real-world scenarios.

1 INTRODUCTION

Electrical and electronics engineering (EEE) embodies a profound synthesis of theoretical knowledge and practical application, serving as the backbone of modern digital and power technological advancements (Bose, 2000; 2020; Irwin & Nelms, 2020). From designing intricate circuitry to advancing power systems, this discipline demands rigorous logical reasoning and a deep understanding of physical laws (Brophy & Voigt, 2014; Saadat et al., 037 1999). Addressing problems in EEE requires that researchers and engineers not only grasp the related theoretical 038 knowledge but also comprehend the associated visual contexts, such as circuit diagrams and signal waveforms. 039 Leveraging machine learning models equipped with robust knowledge and reasoning capabilities, alongside ac-040 curate perception of visual contexts, can significantly enhance various aspects of our lives. These models can aid 041 in intricate hardware design processes (Chang et al., 2023; Liu et al., 2023b; Wu et al., 2024), optimize opera-042 tions within the electric energy sector (Majumder et al., 2024), drive innovation by proposing novel approaches to traditional scientific challenges (Taylor et al., 2022), and assist in solving complex educational problems. 043

044 Recent Large Language Models (LLMs) (Brown, 2020; Jiang et al., 2024; Achiam et al., 2023; Chiang et al., 2023; 045 Touvron et al., 2023) and Large Multimodal Models (LMMs) (Team et al., 2023; Liu et al., 2024b; Zhang et al., 2023; Dai et al., 2023) have achieved much progress and demonstrated remarkable capabilities in various domains, 047 e.g., mathematical reasoning (Yue et al., 2023; Yu et al., 2023) and general science (Lu et al., 2022a). To evaluate 048 the abilities of these foundation models, various specialized or versatile benchmarks (Lu et al., 2023; Zhang et al., 049 2024c; Yue et al., 2024a) have been developed. However, the reasoning ability of these foundation models on 050 engineering problems with visual contexts has not been systematically examined. Therefore, to better harness the potential of foundation models, it is crucial to develop a new benchmark specific to engineering problems, and we 051 select EEE as our case study for reasons mentioned before. This will facilitate the evaluation of LLMs and LMMs 052 in their ability to tackle rigorous engineering reasoning tasks, thereby advancing research progress in this field.

Compared with other subjects such as mathematics, the visual contexts in EEE are often more abstract and heav ily logic-oriented. Solving EEE problems demands specialized technical knowledge, as illustrated in Figure 1.
 Specifically, unlike mathematical problems (Lu et al., 2023; Zhang et al., 2024b; Wang et al., 2024b) which might
 involve clear numerical data and operations, visual representations in EEE, such as circuit diagrams, are intricate and logical, often containing minimal textual information (more example images can be found in Appendix F).

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Figure 1: Comparison between EEE-Bench and MathVista problems: EEE problems feature significantly more complex and intricate visual information compared to mathematical problems, requiring specific technical knowl-edge to interpret diagrams effectively.

Hence effective problem-solving in this domain requires a deep understanding of the logical relationships between
 different components of the diagram and the application of specific technical knowledge to interpret these visuals.

In view of the above, the proficiency of existing LMMs in mathematical domains does not guarantee their effectiveness in EEE tasks. Owing to the same cause, existing benchmarks in other domains (Lu et al., 2022b; 2023; Zhang et al., 2024b; Wang et al., 2024b; Yue et al., 2024a; Yun et al., 2024; Doris et al., 2024) also lack some necessary rigor to accurately faithfully inspect LMMs' problem-solving capability in challenging real-world scenarios where the visual context is crucial but involves serious complexity. Consequently, there is a pressing need for a specialized benchmark focused on EEE to thoroughly assess the multimodal reasoning abilities of LMMs within this specific field as well as to provide a broader outlook of their problem-solving capabilities in these practical engineering problems in the real world.

092 To this end, we present EEE-Bench, a pioneering multimodal electrical and electronics engineering (EEE) reason-093 ing benchmark in visual contexts. To ensure that EEE-Bench encompasses a thorough range of knowledge in EEE, 094 we initially identified ten pivotal topics for problem collection: (1) Digital Logic Circuits and Microprocessor De-095 sign, (2) Circuit Theory and Network Analysis, (3) Analog Circuits, (4) Power Electronics and Power Systems, (5) 096 Signals and Systems, (6) Communication Systems, (7) Control Systems, (8) Electronic Devices, (9) Electrical Ma-097 chines, and (10) Electromagnetics. These topics comprehensively cover both theoretical foundations and practical applications within EEE. When collecting problems for EEE-Bench, we include a broad range of visual contexts 098 such as electric and digital circuits, system diagrams, abstract scenes, electronic component images, and assorted 099 tables, charts, and plots. It's important to note that many figures within EEE-Bench feature combinations of these 100 visual contexts, enhancing their complexity and educational value. Overall, EEE-Bench comprises 2,860 entirely 101 new problems. 102

103 We conduct extensive experiments using EEE-Bench to assess the reasoning abilities of 17 leading foundation models, including both open-source (Chen et al., 2024a; Liu et al., 2024a;b) and closed-source (OpenAI, 2024; 104 Team et al., 2023). Figure 2 illustrates the overall experimental results. We discover that most existing LMMs 105 struggle to understand EEE diagrams and perform poorly on EEE-Bench. Our results show that GPT-40 (OpenAI, 106 2024) achieves the best overall performance across different topics with 46.78% accuracy. Notably, closed-source 107 models generally outperform open-source models. When evaluating performance across various subjects, we 108 observed that many closed-source models excel in subjects with straightforward visual contexts but require signif-109 icant computational resources, such as Electronic Devices. However, these models tend to struggle with subjects 110 that involve complex visual diagrams, such as Circuit Theory and Network Analysis. These findings underscore 111 the proficiency of closed-source LMMs in numerical computation, but also reveal their limitations in processing 112 intricate visual information. Through the fine-grained error analysis, we found that current LMMs struggle to 113 understand EEE diagrams and reason effectively. Taking GPT-40 as an example, we found that over 50% of the 114 errors stem from reasoning issues, and 26.5% are due to errors in image perception. These findings suggest that better EEE visual understanding capabilities and more robust EEE reasoning for LMMs could be the potential for 115 future advancement in addressing multi-modal EEE problems.



Figure 2: Overview of performance of left: open source models and right: close source models.

Lastly, we analyze which modality—vision or text—LMMs predominantly rely on. Our investigation revealed a 'laziness' phenomenon within existing LMMs. Specifically, when presented with spurious captions that contradict the accompanying images, LMMs tend to disregard essential visual information, relying instead on the textual content, even if it is misleading. This tendency leads to flawed reasoning processes within the models. Consequently, augmenting original question text with such spurious captions results in significant accuracy declines—7.79% for GPT-40 and 6.78% for Gemini-Pro 1.5 on the EEE-Bench. These results reveal that existing LMMs mainly rely on text information, and intriguingly, they may overlook visual information when it is explicitly provided in text.

The contributions of this paper can be summarized as follows:

- We introduce EEE-Bench, a novel multimodal benchmark designed for assessing the reasoning abilities of LMMs in electrical and electronics engineering (EEE) problems. EEE-Bench consists of 2860 samples spanning 10 essential subjects in EEE, featuring a diverse range of visual contexts such as electric and digital circuits, system diagrams, and others. This benchmark is specifically crafted to evaluate how well LMMs can handle complex visual and logical challenges within the EEE field.
- We conduct extensive experiments using EEE-Bench to assess the reasoning abilities of 17 leading opensource and closed-source foundation models. We found that most existing LMMs struggle to deal with EEE problems, especially in subjects with complex visual contexts, yielding an average performance ranging from 19.48% to 46.78%. We also demonstrate that reasoning errors and image perception errors are the main problems for current LMMs. These findings provide insights for future improvement.
- We further explore which modality—text or vision—current LMMs primarily rely on. Our research identifies a 'laziness' phenomenon in these models: LMMs will not try to read images if relevant visual information for solving problems appears in the text, even if this extra-textual information is spurious. Our experiments show that introducing additional misleading captions into the text leads to a 7.79% drop in accuracy for GPT-40 on the EEE-Bench.

2 THE EEE BENCHMARK

In this section, we introduce EEE-Bench. First, we introduce our data collection process in subsection 2.1. Next, we provide a summary of EEE-Bench in subsection 2.2. Lastly, we provide a high-level analysis in subsection 2.3; we leave detailed analysis to subsection 3.2 and subsection 3.3.

2.1 DATA COLLECTION

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Guidelines. As our general principle is to establish a challenging real-world-oriented benchmark capable of assessing both visual understanding and logical reasoning with integrated multimodal knowledge, we adhere to the following guidelines for initial data collection: 1) questions with high-resolution and context-rich images (diverse complex patterns, domain-specific markings, etc); 2) problems that require logical reasoning steps (calculations, cross-domain information integration) to solve in addition to visual comprehension; 3) problems with deterministic answers for robust evaluation (multiple choices questions and free-form questions requiring answer no longer than one word as did in Lu et al. (2023)); 4) balanced collection source, sub-domain representation, and problem type.

Table 1: Key Statistics of EEE-Bench.

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Figure 3: **Subject Distribution of EEE-Bench.** DLC&MPD: Digital Logic Circuits and Microprocessor Design, PS: power systems. NA: network analysis





Collection and curation. We collect all our questions from official EEE exams as well as verified online sources 192 in a multimodal setting (see subsection 2.2 for summary details). Note that as our work is first in this direction, 193 no existing dataset or benchmark is available, hence all questions are newly collected. Example problems can be 194 found in Figure 1, Figure 4, and Appendix I. For data curation, we employ a two-stage filtering process. To ensure 195 the solution quality, we first filter for questions appearing in at least two distinct sources having identical solutions. 196 To ensure the significance of visual input, we subsequently adopt methods similar to Yue et al. (2024b) where two 197 trials are run using text-only GPT-4 (OpenAI, 2024) in which questions with two correct answers are eliminated. 198 These processes result in 2860 high-quality examples across ten sub-domains. Two final quality checks for typos, 199 image resolution, and prompt completeness were also conducted by graduate students.

Release. We release the benchmark as organized in two formats: 1) one complete set and 2) sub-domains.
 We also release metadata annotations denoting question title (stored in markdown format), image path, answer, question type, image ID, source, source image ID, topic, query, answer type, and choices in JSON format similar to Lu et al. (2023). For the question title, we also prepend an instructional prompt, see Appendix C for details. We also release the complete evaluation source code.

207 2.2 BENCHMARK SUMMARY

The key statistics of EEE-Bench are shown in Figure 1 and subject distribution is shown in Figure 3. Our bench-209 mark consists of a total of 2860 examples divided into 10 diverse but essential sub-domains. We first summarize 210 general statistics. Questions in our benchmark are categorized into two types similar to Lu et al. (2023): multiple 211 choice and free-form, counting 2059 and 801, respectively. Regarding answer type, four forms are present: text 212 (single word) represents the largest group of 2059 questions, 595 are float, 204 are integer, and 2 are list. The 213 average token length for question text is 306. Next, we provide a breakdown of the 10 sub-domains. Digital 214 Logic Circuits and Microprocessor Design (496 examples) assess the design and functionality of circuits central 215 to computing systems like processors and memory. Electronic Devices (219 examples) evaluate the understand-216 ing of components such as diodes and transistors, foundational to all electronics. Communication Systems (101 examples) assess signal transmission and processing, crucial for wireless networks and satellite communications. 217 Signals and Systems (138 examples) evaluate the mathematical representation and manipulation of signals, funda-218 mental for control systems and digital signal processing. *Electrical Machines* (161 examples) assess knowledge 219 of devices like motors and generators, essential for power generation and industrial applications. *Electromagnet*ics (102 examples) evaluate the principles of electromagnetic fields and waves, vital for RF communication and 221 antenna design. Control Systems (239 examples) assess feedback mechanisms and system stability, critical for au-222 tomation and robotics. Power Electronics and Power Systems (229 examples) evaluate the conversion and control 223 of electrical power, key to renewable energy systems and power grids. Circuit Theory and Network Analysis (592 224 examples) assess both AC and DC circuit analysis, forming the foundation of all electrical applications. Lastly, 225 Analog Circuits (583 examples) evaluate continuous-time circuit design, essential for applications like audio, RF, 226 and sensor interfaces. We leave more detailed descriptions of these 10 subdomains to Appendix G.

228 2.3 BENCHMARK ANALYSIS

Overall quality. Benchmarks catered toward LMM evaluations should provide unbiased, fair, and exhaustive
 evaluations. EEE-Bench achieves these qualities by ensuring diversity in terms of both type and sub-domain. The dynamic question settings reduce the potential for bias, and the wide coverage of sub-domains captures the



Figure 4: Comparison between solutions of logical circuits and circuit theory. Logic Circuits demand a thorough comprehension of logical structuring and timing analysis, yet they do not heavily rely on computation. In contrast, problems of circuit theory involve solving complex equations and applying numerical methods to analyze circuits.

diverse nature of engineering problems while ensuring a comprehensive and fair representation of the EEE domain.
More importantly, the diverse nature of EEE-bench also enables granular evaluation of model performance, thus
providing a framework for more nuanced by-type and by-sub-domain analysis (subsection 3.2), readily unveiling
the underlying strengths and weaknesses of different models. Varied difficulty levels are also introduced to best
mimic real-world situations and enhance the interpretability of the assessment. We note that the best-performing
proprietary model GPT-40 (OpenAI, 2024) and open-source model InternVL2-26B (Chen et al., 2024b) set at
46.78% and 26.89% overall accuracy respectively, while the averages of all proprietary models and open-sourced
models are 35.28% and 23.19% respectively. For more detailed results and analysis, please refer to subsection 3.2.

264 Comprehensive evaluation of LMM's various abilities. EEE-Bench encompasses 10 pivotal subjects within 265 the field of electrical and electronics engineering, extending from circuit analysis to control systems. Each subject 266 demands specialized capabilities for addressing unique challenges. For instance, as shown in Figure 4, tackling 267 problems within the Digital Logic Circuits and Microprocessor Design discipline requires models to deeply un-268 derstand intricate logic relationships in digital circuits and reason effectively. These problems demand a thorough comprehension of logical structuring and timing analysis, yet they do not heavily rely on computational power 269 or advanced mathematical computations. In contrast, many challenges from Circuit Theory and Network Anal-270 ysis may present less complexity regarding logic understanding but require extensive computational processing 271 and the use of sophisticated mathematical tools. This involves solving complex equations and applying numerical 272 methods to analyze and interpret circuit behaviors and responses under various conditions. A detailed introduction 273 about the characteristics of each subject's problems and the required ability for LMMs to solve them are discussed 274 in Appendix H. The juxtaposition of these disciplines within EEE-Bench highlights the diverse skill sets needed to 275 address the spectrum of issues prevalent in the field of electrical and electronics engineering, therefore effectively 276 examining various abilities of existing LMMs.

Significance of vision in EEE-Bench. Meaningful multimodal benchmarks should place largely equal weights
on both visual and language inputs. Recent studies have unveiled that some previous multimodal benchmarks
lack visual depth and complexity thus making their visual input ad-hoc (Tong et al., 2024; Yue et al., 2024b). In
EEE-Bench, we ensure that vision plays an indispensable role. First, as shown in Table 2, the text-only baseline
with GPT-4 results in a 21.26% and 14.69% drop in accuracy compared to GPT-40 and GPT-4V respectively with
complete input. Second, we found that the improved text-only-with-caption baseline merely improves accuracy by
2.7% with GPT-4 (Table 2). These results highlight the significance and indispensability of vision in EEE-Bench.

3 EXPERIMENTS

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In this section, we conduct a comprehensive evaluation of 17 existing LLMs and LMMs on EEE-Bench. subsection 3.1 introduces the experimental setup. Subsequently, subsection 3.2 presents the quantitative results. Finally, section 3.3 provides a detailed, fine-grained error analysis.

Model	ALL	EMag	PEPS	SS	EMac	DLC	CorS	AC	CTNA	ComS	ED
Random Chance	17.45	28.43	19.65	15.22	18.01	18.55	15.90	18.18	16.89	15.84	10.50
				LLM	s (text inj	out)					
GPT-4	25.52	29.41	25.33	25.36	26.71	28.23	27.20	26.59	22.47	28.71	19.18
GP1-4 w/ caption	28.22	28.43	28.82	26.81	31.06	31.25	25.10	25.21	27.20	34.65	30.59
				Open-s	source LN	MMs					
Llava-1.6-7B	21.36	32.35	27.51	26.09	26.09	24.60	20.50	19.55	19.09	13.86	11.42
Llava-1.6-13B	20.73	26.47	20.96	17.39	21.74	26.01	21.34	18.70	21.11	13.86	14.16
SPHINX-v2-1k	19.48	18.63	21.40	20.29	18.01	25.40	23.01	18.01	17.74	14.85	11.87
MiniCPM-V-2.6	25.21	26.47	24.45	18.84	36.02	34.07	27.62	22.98	21.45	21.78	16.44
InternVL2-26B	26.89	38.24	29.26	26.81	31.06	28.02	23.01	26.93	24.66	20.79	26.48
DeepSeek-VL	22.31	23.53	26.20	17.39	21.74	29.23	25.52	21.10	18.58	23.76	14.61
GLM-4V-9B	24.06	26.47	23.14	22.46	27.95	26.01	30.13	23.50	19.76	22.77	24.66
InternLM-XC2.5	23.85	28.43	18.34	23.91	24.84	27.82	24.27	23.50	21.45	28.71	22.37
Phi3V	24.90	27.45	25.76	25.36	28.57	31.45	27.62	22.81	21.28	24.75	17.35
				Closed-	source L	MMs					
GPT-40	46.78	50.98	47.60	46.38	49.69	47.78	46.03	44.60	40.88	60.40	56.16
GPT-4V	40.21	44.12	38.86	44.93	32.30	42.94	41.00	37.74	36.32	48.51	48.86
GPT-4o-mini	36.99	38.24	34.50	42.03	30.43	39.52	39.75	33.62	32.77	43.56	49.32
Gemini-Pro 1.5	41.99	50.00	46.29	42.75	36.65	38.71	46.03	41.85	38.34	54.46	44.75
Gemini-Flash 1.5	33.95	37.25	32.75	35.51	35.40	35.89	40.59	30.87	31.93	42.57	29.68
Qwen-VL-Max	25.73	25.49	24.45	22.46	26.71	28.02	26.36	26.24	24.66	26.73	23.74
Qwen-VL-Plus	21.33	26.47	22.71	13.77	23.60	25.40	19.67	21.10	20.78	16.83	17.35

Table 2: Comparison of model performances across various EEE subjects. Subjects: EMag: Electromagnet-315 ics, PEPS: Power Electronics and Power Systems, SS: Signals and Systems, EMac: Electrical Machines, DLC: 316 Digital Logic Circuits and Microprocessor Design, CorS: Control Systems, AC: Analog Circuits, CTNA: Circuit Theory and Network Analysis, ComS: Communication Systems, ED: Electronic Devices. The highest accuracy 317 318 for **closed-source** and **open-source** LMMs is marked in **red** and **blue** respectively.

3.1 EXPERIMENT SETUP

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322 Model selection. We evaluate a total of 1 LLM and 16 LMMs against EEE-Bench. The abundant model se-323 lection captures the diversity of LMMs today and ensures a thorough and comparable assessment. In detail, the LMM set includes (a) 9 open-source LMMs: LLaVA1.6-7B, LLaVA-1.6-13B (Liu et al., 2023a; 2024b), 324 DeepSeek-VL-7B (Lu et al., 2024), Phi3-Vision-4.2B (Abdin et al., 2024), MiniCPM-Llama3-V 2.6 (Yao et al., 325 2024), SPHINX-v2-1k (Liu et al., 2024a), InternVL2-26B (Chen et al., 2024a;b), GLM-4V-9B (GLM et al., 2024), 326 and InternLM-XC2.5 (Zhang et al., 2024a), (b) 7 closed-source LMMs: GPT-4o (OpenAI, 2024), GPT-4o-mini 327 (OpenAI, 2024), GPT-4V (OpenAI, 2023), Gemini 1.5 Pro, Gemini 1.5 Flash (Reid et al., 2024; Team et al., 328 2023), Qwen-VL-Max and Qwen-VL-Plus (Bai et al., 2023). We provide example responses from various models 329 in Figure 41 and Figure 42. To further ground the impact of vision in LMMs, we provide two additional input-only 330 evaluation baselines using GPT-4 (Achiam et al., 2023): 1) a text-only baseline where the visual inputs are entirely 331 hidden and 2) an improved baseline of text-only input but with image captions generated by GPT-40. The prompt 332 for caption generation is available in Appendix C. More details about all models can be found in Appendix E. 333

334 **Evaluation.** We utilize an evaluation pipeline similar to MathVista (Lu et al., 2023). Raw responses are first 335 generated from LMMs and then processed by GPT-4o-mini to extract the concise answers given an exemplary 336 system prompt. Finally, accuracy is obtained through calculation against the ground truth. 337

Implementation details. We evaluate all models in a zero-shot manner for better generalization examination. 339 We run each evaluation setting twice for each LMM and record their average scores for the final report. All 340 experiments for open-source models are conducted on NVIDIA A100 GPUs. We also provide all hyperparameters 341 and model setups used for evaluations in Appendix E. 342

344 3.2 EXPERIMENT RESULTS

In this section, we compare the performance of 17 open-source and closed-source models. We report the overall 346 accuracy and the accuracy among each subject. The results are shown in Table 2. 347

³⁴⁸ Finding 1: Existing LMMs struggle to address EEE problems.

349 The results presented in Table 2 highlight that existing LMMs can 350 not deal well with EEE problems in visual contexts. A represen-351 tative failure case is shown in Figure 42. For example, GPT-40 352 achieves the highest average accuracy of just 46.78% (less than half), and the average accuracies of proprietary and open-source 353 models are only 35.28% and 23.19%, respectively. These results 354 indicate that current LMMs are inadequate in providing satisfac-355 tory assistance for real-world engineering tasks with their existing 356 performance levels. 357

Finding 2: Open-source models see superior generalization
compared to closed-source models. Similar to prior works
on benchmarking the performance of LLMs and LMMs in mathematics and sciences (Lu et al., 2023; Yue et al., 2024a), we found
it evident that a significant performance disparity exists between



Figure 5: Error distribution of the wrong results from GPT-40 on EEE-Bench.

363 closed-source and open-source models, as shown in Table 2.. The top two best-performing closed-source LMMs, 364 GPT-4o and Gemini-Pro 1.5, significantly outperform their open-source counterparts. For instance, GPT-4o, 365 the best-performing closed-source LMM, has an average accuracy of 46.78%, while the highest-scoring opensource LMM, InternVL2-26B, achieves only 26.89%-a gap of nearly 20 percentage points. Moreover, even the 366 lightweight closed-source models, GPT-4o-mini and Gemini-Flash 1.5, surpass all open-source LMMs in perfor-367 mance. This discrepancy not only underscores the superior generalization capability of state-of-the-art (SOTA) 368 closed-source models but also underscores the pressing need for the development of open-source LMMs that are 369 proficient in EEE tasks. 370

Finding 3: Diverse subdomains present different challenges. As discussed in subsection 2.3, problems across various subjects demand specific capabilities for effective resolution. This section delves into the performance of existing LMMs across diverse subjects and discusses their strengths and weaknesses.

It is noteworthy that most closed-source LMMs excel in handling problems related to Communication Systems and Electronic Devices, yet they perform significantly poorer on problems from Analog Circuits and Circuit Theory and Network Analysis. For instance, the best-performing LMM GPT-40 achieves average accuracies of 60.40% and 56.16% in Communication Systems and Electronic Devices respectively, which are substantially higher than the overall average accuracy of 46.78%. In contrast, its performance drops to 44.60% and 40.88% in Analog Circuits and Circuit Theory and Network Analysis, respectively, both of which fall below the overall average.

Problems within Communication Systems and Electronic Devices typically present straightforward visual infor-381 mation, yet solving them demands considerable computational effort. Conversely, problems from Analog Circuits 382 and Circuit Theory and Network Analysis often feature complex visual contexts, such as intricate circuit diagrams, 383 necessitating the use of advanced mathematical and computational tools. Thus, tackling issues in these domains 384 requires not just strong numerical capabilities but also sophisticated vision recognition and reasoning skills. This 385 performance disparity highlights that while many existing closed-source LMMs are adept at managing computationally intensive tasks due to their robust numerical calculation capabilities, they struggle with EEE problems that 387 require more nuanced vision recognition and complex reasoning abilities. This suggests a crucial area for further 388 development in enhancing the vision and reasoning capabilities of LMMs to better handle the full spectrum of 389 EEE challenges. 390

Conversely, open-source LMMs face challenges in handling tasks related to Communication Systems and Electronic Devices, despite the simplicity of the associated visual contexts. This performance discrepancy between open-source and closed-source LMMs in these domains underscores a significant shortfall in the computational capabilities of the open-source models. Urgent development is needed to enhance the computational efficiency and numerical problem-solving abilities of open-source LMMs.

3.3 Error Analysis

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In this section, we provide an in-depth analysis of the common errors observed in evaluations on EEE-Bench using GPT-40 as an example. Figure 5 shows the breakdown by error measured by 6 types: reasoning error, image perception error, question misunderstood error, knowledge error, calculation error, and rejection to answer. We focus our analysis on the two largest error groups, **reasoning error** and **perception error**, constituting **50.3**% and **26.5**% of total error respectively.

Lack of reasoning. These happen when LMMs can read the image but cannot reason correctly to arrive at the
 answer. For instance, on the right of Figure 6, the LMM correctly reads the location of contact C but fails to
 consider the location of resistor *R* in the overall circuit, thus leading to the wrong answer.



Figure 6: Error examples of response from GPT40. Left: Image Perception Error. Right: Reasoning Error. Error part is marked with red color.

430 Lack of visual understanding. These happen when LMM fails to answer correctly due to misunderstandings of the image compositionally. Concretely, the circuit diagram on the left of Figure 5 shows a filter circuit using 432 an operational amplifier with multiple feedback loops involving resistors and capacitors. In such cases even if the 433 explanation is fine the verdict is wrong as the diagram is more complex than current LMMs can handle.

434 The examples above clearly underline the challenge of engineering problems to LMMs. We provide more of 435 such instances in Appendix I. Compared to other domains such as mathematics, these results demonstrate that 436 engineering problems are intrinsically more complex and dynamic as components in domains such as electric 437 engineering could be arranged in very different but meaningful ways or layered up to form more complicated 438 diagrams whereas their counterparts in, for example, mathematics are mostly stagnated and fixed. On the other 439 hand, it highlights the fact that LMMs struggle to understand electric engineering diagrams, and are especially 440 prone to increased visual complexity and details such as resisters, signs, etc. Overall, it indicates that solving 441 these electric engineering problems requires more delicate incorporations of both visual and textual inputs.

4 DISCUSSION

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445 **The unique challenge of EEE problems.** Here we address the unique challenge of visual complexity in EEE-446 Bench. subsection 3.2 demonstrates that even SOTA LMMs struggle to understand and reason about EEE prob-447 lems. To understand this phenomenon further, we design and conduct a simple experiment which is to provide 448 additional information in the prompt for assistance. Concretely, we generate for each image a caption X_c using GPT-40 to let it describe very detailed key visual information related to potential EEE problem-solving (the prompt 449 for caption generation is provided in Appendix C) and prepend such caption to the original question prompt X_q 450 such that the new query is $(X_{ins} + X_c) + X_q$ where X_{ins} is a system instruction prompt which reads "Image 451 caption context:". Surprisingly, as shown in Table 3, the improvements on the EEE-Bench with such caption are 452 negative across 7 out of 10 subdomains, with an average performance change of -1.43% using GPT-40. Figure 29 453 and Figure 30 show two of such examples. Technically speaking, captions generated by GPT-40 should include 454 key and correct information from the images. However, in our case, it is apparent that such knowledge fails to 455 be useful and even provides negative guidance in some cases. Importantly, such an effect evidently implies the 456 intense difficulty of the images in EEE-Bench, which we believe is due to the high level of abstraction and ver-457 satility as well as the abundance of domain-specific details contained in these images, especially compared to 458 other domains like mathematics. More intriguingly, it raises a more significant question about LMMs: do LMMs 459 rely more on vision or text?

461 Your LMM might be lazy. In this section we attempt to uncover the underlying cause of the phenomenon raised 462 above. To explore this issue, we design a straightforward experiment that prepends, instead of the accurate caption X_c , a spurious caption X'_c which contains a spurious caption of the image augmented from the original caption 463 by GPT-4 (the prompt for spurious caption generation is provided in Appendix C). We intentionally make such



describing a function like shown in Figure 7. It is important to note that we ask specifically in our query for LMMs 492 to answer based on the *figure* or *image* such that the captions merely serve as additional information. We display 493 results on EEE-Bench in Table 3 and on MathVista (Lu et al., 2023) in Table 7. Interestingly, across the board, 494 the results show a significant negative impact, measuring a 7.79% and 8.4% drop on EEE-Bench and MathVista 495 respectively using GPT-40, where the same can be found with Gemini-Pro 1.5. For example, Figure 7 shows 496 a case on EEE-Bench where LMMs fail to reason correctly due to spurious instruction which merely changes 497 "increasing" into "decreasing", even if the function in the image is clearly increasing. More of such examples are 498 displayed in Figure 31 through Figure 38 for EEE-Bench and in Figure 39 through Figure 40 for MathVista for reference. These results demonstrate that LMMs are severely distracted by the spurious prompt. On one hand, 499 spurious captions may indeed hallucinate LMM's reasoning process. On the other hand, the instruction clearly 500 states answering questions with the *figure* or *image*. This observation unveils a key shortcoming of LMMs that 501 they may simply be lazy when both visual and textual inputs are given. We note that a recent work (Shi et al., 502 2023) indeed finds that LLMs are easily disturbed by irrelevant content. We thus believe that the shortcoming 503 revealed by our study is noteworthy for further detailed investigations as it is a major issue in many practical 504 cases. 505

5 RELATED WORKS

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509 5.1 LARGE MULTIMODAL MODELS

Following the rapid development and success of Large Language Models (LLMs) (Brown, 2020; Jiang et al., 2024; 511 Touvron et al., 2023; Wei et al., 2021), Large Multimodal Models (LMMs) have been constructed by integrating 512 LLMs with large vision encoders (Radford et al., 2021; Caron et al., 2021; Oquab et al., 2023; Chen et al., 513 2021). Notably, closed-source versatile LMMs such as GPT-40 (OpenAI, 2024) and Gemini-Pro 1.5 (Team et al., 514 2023) have achieved exceptional visual reasoning capabilities across various domains, including Visual Question 515 Answering (Li et al., 2024a) and Mathematics (Lu et al., 2023). In response to the need for publicly accessible 516 versatile LMMs, several open-source models such as LLaVA (Liu et al., 2024b) have been developed (Li et al., 517 2022; Liu et al., 2024b; 2023a; Gao et al., 2023; Zhang et al., 2023; Li et al., 2023; Chen et al., 2023a; Ye et al., 518 2023; Tong et al., 2024). Moreover, specialized LMMs finetuned on specific subdomain data (Wang et al., 2023a; 519 Hu et al., 2021) have been introduced, demonstrating performance on par with closed-source models in specific subject areas like Mathematics (Shi et al., 2024; Zhang et al., 2024d; Zhuang et al., 2024) and chart (Meng et al., 520 2024; Hu et al., 2024). Recent efforts have also focused on leveraging large models for engineering tasks, such as 521 chip design (Bose, 2000; 2020; Irwin & Nelms, 2020; Chang et al., 2024a) and optimizing operations in the energy

522	Model	ALL	EMag	PEPS	SS	EMac	DLC	CorS	AC	CTNA	ComS	ED
523					(GPT-40						
524	GPT4o	46.78	50.98	47.6	46.38	49.69	47.78	46.03	44.6	40.88	60.4	56.16
525	w/ caption	45.35	48.04	41.48	44.93	44.72	43.75	44.35	46.31	42.23	48.51	57.99
526	Δ	-1.43	-2.94	-6.12	-1.45	-4.97	-4.03	-1.68	+1.71	+1.35	-11.89	+1.83
527	w/ spurious caption	38.99	50.00	38.43	44.93	36.02	40.12	38.91	38.42	33.11	45.54	44.75
528	Δ	-7.79	-0.98	-9.17	-1.45	-13.67	-7.66	-7.12	-6.18	-7.77	-14.86	-11.41
529					Gen	nini-Pro 1	.5					
530	Gemini-Pro 1.5	41.99	50	46.29	42.75	36.65	38.71	46.03	41.85	38.34	54.46	44.75
531	w/ spurious caption	35.21	46.08	41.92	38.41	37.89	36.9	38.49	31.39	29.39	38.61	36.07
532	Δ	-6.78	-3.92	-4.37	-4.34	+1.24	-1.81	-7.54	-10.46	-8.95	-15.85	-8.68

Table 3: Performance comparison of GPT-40 and Gemini-Pro 1.5 with and without spurious captions. Positive changes are in blue and negative changes in red.

sector (Majumder et al., 2024). However, the reasoning capabilities of existing LMMs in visual contexts have not yet been thoroughly examined for electrical and electronics engineering (EEE) problems. Therefore, this paper proposes EEE-Bench to comprehensively evaluate the EEE multimodal reasoning abilities of current LMMs.

540 5.2 MULTIMODAL BENCHMARKS 541

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542 As Large Language Models (LLMs) and Large Multimodal Models (LMMs) continue to evolve rapidly, the cre-543 ation of comprehensive and challenging benchmarks to assess their capabilities has become increasingly vital 544 (Chang et al., 2024b; Cui et al., 2024). These benchmarks are indispensable for evaluating the strengths and lim-545 itations of these models, thereby facilitating their ongoing development and refinement. To measure the abilities 546 of LLMs, various text-only benchmarks have been introduced (Hendrycks et al., 2020; 2021; Zheng et al., 2023; Zellers et al., 2019; Jimenez et al., 2023). For vision and language benchmarks, early efforts primarily concen-547 trated on general-purpose Visual Question Answering (VQA) tasks (Mathew et al., 2021; Gurari et al., 2018; 548 Antol et al., 2015; Goyal et al., 2017; Singh et al., 2019; Hudson & Manning, 2019; Mathew et al., 2021; Marino 549 et al., 2019), which may not sufficiently test the reasoning abilities of today's more advanced LMMs. To pro-550 vide a multi-faceted evaluation, several benchmarks have been introduced, including specialized ones (Lu et al., 551 2023; Zhang et al., 2024c; Qiao et al., 2024; Wang et al., 2024a;c; Li et al., 2024b; Lu et al., 2021) and versatile 552 benchmarks (Li et al., 2024a; Liu et al., 2023c; Liang et al., 2024; Saikh et al., 2022; Yue et al., 2024a; Wang 553 et al., 2023b; Chen et al., 2023b). For instance, MathVista (Lu et al., 2023) assesses the mathematical reasoning 554 capabilities of LMMs across various visual contexts. However, the visual context in mathematical problems is 555 much less complex compared with real-world engineering problems that appeared in EEE-Bench. MMMU (Yue 556 et al., 2024a) tackles college-level questions that require intricate, domain-specific knowledge across multiple subjects. Although MMMU also includes some EEE problems, its scope in terms of problem variety and subject 558 coverage is limited, which may not thoroughly evaluate the reasoning capabilities of LMMs on EEE tasks. Doris et al. (2024) benchmarks LMMs' understanding of engineering requirement documents, yet they are not directly 559 related to solving engineering problems. To the best of our knowledge, we respectively believe EEE-Bench, which 560 comprises 2860 meticulously curated problems from ten pivotal EEE subjects, is the first in the direction to offer 561 a robust and comprehensive assessment of LMMs' reasoning abilities in complex visual contexts within EEE. 562

6 CONCLUSION

566 This study focuses on benchmarking modern LMMs' performance on EEE problems, an important representation 567 of the border engineering domain and a high-impact subject in our daily lives (section 1). We start by creating a pioneering electric engineering-based benchmark termed EEE-Bench consisting of 2860 hand-picked and carefully curated questions covering 10 subdomains of electric engineering in subsection 2.2. We perform evaluations and in-depth analysis of 17 open and closed-source LLMs (1) and LMMs (16) on EEE-Bench, such diverse coverage 570 ensures a thorough and comparable assessment (subsection 3.2). Importantly, we conclude that, in the field of 571 EEE, as well as engineering in general, today's foundation models still struggle to understand and reason through 572 intricate EEE questions in visual context (section 3.3), revealing the unmet promise of human-level LMMs in this 573 domain. Our analysis shows that such deficiency lies in the unique challenge of engineering problems compared 574 to other domains, namely the high level of **abstraction** and **versatility**, as well as **domain-specific information** 575 (section 4). Furthermore, our study reveals an interesting "laziness" phenomenon of LMMs, namely the tendency 576 of overly reliance on and easy distraction by textual input thus overlooking visual context, suggesting a limita-577 tion noteworthy for future research (section 4). We hope EEE-Bench can advance the research for more capable 578 LMMs for EEE and for engineering by providing a robust and comprehensive evaluation tool focusing on both understanding and reasoning while harnessing the bright potential of the usage of LMMs in more complex and 579 real-world scenarios.

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we	provide an additional details for our paper in the following sections.
	Appendix B discusses the broader impact of EEE-Bench.
	Appendix C provides all prompts used in paper.
	Appendix D provides more experimental results.
	• Appendix E provides the information of the models used in experiments and their hyper-parameters.
	Appendix F provides more example images about EEE-Bench.
	• Appendix G provides detailed introduction to the 10 pivotal subjects in EEE-Bench.
	• Appendix H discusses the specific required abilities for LMM to address the challenges in each subject, and shows examples of problem solutions for each subject.
	• Appendix I provides more qualitative examples of error analysis.
	• Appendix J provides more examples of the laziness phenomenon of existing LMMs.
В	BROADER IMPACT
ap pro	abilities across the full engineering landscape. We plan to carry out such studies and extend EEE-Bench to ader engineering domains in future works.
E <b>th</b> ion Ve hat	<b>ics statement.</b> We ensure that EEE-Bench complies with legal and ethical guidelines throughout its construc- process, with no violations. We provide fair compensation to all annotators and graduate students involved. collect problems from free-access public open exams ¹ and resources under the CC Licenses ²³ . We guarantee EEE-Bench is solely for academic research purposes, and we uphold the strict prohibition of any commercial
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918 The prompt for spurious caption generation using GPT-4 on EEE-Bench is as follows:

I will give a caption of an Electrical and Electronics Engineering (EEE) problem image and the associated question. Please help me rewrite the image caption so that it contains incorrect information, which could lead to an incorrect solution. Please only output the revised incorrect caption. Please do not change name of variables, e.g.,
F, G. Please Do not change too much. Here are some examples of how you can introduce incorrect information into an Electrical and Electronics Engineering (EEE) image caption to potentially mislead a model into generating a wrong solution:

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¹https://gate2025.iitr.ac.in/

²https://www.allaboutcircuits.com/worksheets/

³https://ocw.mit.edu/

928 Table 4: The task instructions for different question and answer types in answer extraction. Here, Float (1) refers 929 to a floating-point number with one decimal place, Float (2) refers to a floating-point number with two decimal places, and Float (3) refers to a floating-point number with three decimal places. 930

Ouestion type	Answer type	Task instruction
multiple shoige	Toxt	Please answer the question and provide the correct option letter, e.g., A,
muniple-choice	Text	B, C, D, at the end.
Free_form	Integer	Please answer the question requiring an integer answer and provide the
1100-101111	Integer	final value, e.g., 1, 2, 3, at the end.
Free_form	Float (1)	Please answer the question requiring a floating-point number with one
Tice-tottili	110at (1)	decimal place and provide the final value, e.g., 1.2, 1.3, 1.4, at the end.
		Please answer the question requiring a floating-point number with two
Free-form	Float (2)	decimal places and provide the final value, e.g., 1.23, 1.34, 1.45, at the
		end.
		Please answer the question requiring a floating-point number with three
Free-form	Float (3)	decimal places and provide the final value, e.g., 1.200, 1.300, 1.400, at
		the end.
Free-form	List	Please answer the question requiring a Python list as an answer and
	List	provide the final list, e.g., [1, 2, 3], [1.2, 1.3, 1.4], at the end.

94 946 947

948 1. Incorrect component identification: Original: "The circuit contains a  $10\Omega$  resistor and a 5V voltage source." 949 Misleading: "The circuit contains a  $100\Omega$  resistor and a 12V voltage source."

2. Wrong power supply voltage: Original: "The circuit is powered by a 5V DC supply." Misleading: "The circuit 950 is powered by a 15V AC supply." 951

3. Inverted polarity for components: Original: "The diode is forward biased in this circuit." Misleading: "The 952 diode is reverse biased in this circuit." 953

4. Incorrect current direction: Original: "The current flows clockwise through the loop." Misleading: "The cur-954 rent flows counterclockwise through the loop." 955

5. Swapping component values: Original: "The capacitor has a capacitance of  $100\mu$ F, and the inductor is 10mH." 956 Misleading: "The capacitor has a capacitance of  $10\mu F$ , and the inductor is 100mH."

957 6. Incorrect assumptions about the circuit operation: Original: "The transistor is in active mode." Misleading: 958 "The transistor is in saturation mode."

959 7. Wrong frequency or waveform type: Original: "The AC signal is a 60Hz sine wave." Misleading: "The AC 960 signal is a 50Hz square wave."

8. Incorrect type of circuit: Original: "This is a simple RC low-pass filter." 961

Misleading: "This is a high-pass filter." 9. Incorrect labeling of nodes or points: Original: "Measure the voltage 962 at node A, which is connected to the positive terminal." Misleading: "Measure the voltage at node A, which is 963 connected to the negative terminal." 964

10. Misleading behavior of the circuit: Original: "The capacitor charges fully after 5 seconds." Misleading: 965 "The capacitor discharges completely after 5 seconds." 966

11. Incorrect power consumption: Original: "The total power consumed by the circuit is 50W." Misleading: "The 967 total power consumed by the circuit is 100W."

968 12. Mislabeling passive vs. active components: Original: "The operational amplifier is used as an active compo-969 nent in this circuit." Misleading: "The operational amplifier is used as a passive component in this circuit."

970 13. Incorrect reading: Original: "Only when A=1, B=1, C=1, F=1." Misleading: "when A=1, B=1, C=1, F=0, 971 when A=0,B=1,C=1, F=1.

972 The prompt for spurious caption generation using GPT-4 on Math-Vista is as follows: 973

I will provide a caption of a Math problem image along with the associated question. Please help me rewrite the 974 image caption so that it contains incorrect information, potentially leading to an incorrect solution. Please only 975 provide the revised incorrect caption. Do not change the names of variables, such as F or G, and avoid making

976 extensive changes. 977

Please do not change the name of variables, e.g., F, G. Please Do not change too much. Please do not change the 978 essential meaning of original text and only change subtle places like values.

979 Below are some examples of how you can introduce incorrect information into a Math problem caption to mislead 980 a model:

981 Incorrect value of constants: Original: 'The equation has a constant value of 3.' Misleading: 'The equation has 982 a constant value of 5.'

983 Wrong interpretation of angles: Original: 'Angle ABC is 90°.' Misleading: 'Angle ABC is 60°.'

984 Incorrect function transformation: Original: 'The function is f(x) = 2x + 3.' Misleading: 'The function is f(x) = -32x - 3.' 985

Wrong area formula: Original: 'The area of the circle is given by  $\pi r^2$ .' Misleading: 'The area of the circle is

Model	Generation Setup
GPT-4	"model": "gpt-4", "temperature": 0, "max_tokens": 1024
GPT-40	"model" : "gpt-4o-2024-08-06", "temperature" : 0, "max_tokens" : 1024
GPT-4V	"model": "gpt-4-turbo", "temperature": 0, "max_tokens": 1024
GPT-4o-mini	"model" : "gpt-4o-mini", "temperature" : 0, "max_tokens" : 1024
Gemini 1.5 Pro	"model" : "gemini-1.5-pro", "temperature" : 0, "max_tokens" : 1024
Gemini 1.5 Flash	"model" : "gemini-1.5-flash", "temperature" : 0, "max_tokens" : 1024
Qwen-VL-Max	"model": "qwen-vl-max", "temperature": 0, "max_tokens": 1024
Qwen-VL-Plus	"model" : "qwen-vl-plus", "temperature" : 0, "max_tokens" : 1024

Table 5: Generating parameters for Closed-Source LMMs.

Table 6: Generating parameters for Open-Source LMMs.

Model	Generation Setup
Llava-1.6-7B	do_sample = False, temperature = 0, max_new_tokens = 1024
Llava-1.6-13B	do_sample = False, temperature = 0, max_new_tokens = 1024
SPHINX-v2-1k	do_sample = False, temperature = 0, max_new_tokens = 1024
MiniCPM-V-2.6	do_sample = False, temperature = 0.1, max_new_tokens = 1024
DeepSeek-VL-7B	do_sample = False, max_new_tokens = 1024
Phi3-Vision-4.2B	do_sample = False, temperature = 0, max_new_tokens = 1024
InternVL2-26B	do_sample = False, temperature = 0, max_new_tokens = 1024
InternLM-XComposer2.5-7B	do_sample = False
GLM-4V-9B	$do_sample = False, max_length = 1024, temperature = 0$

given by  $2\pi r$ .

Incorrect limit definition: Original: 'The limit of the function as x approaches 2 is 4.' Misleading: 'The limit of the function as x approaches 2 is 5. 

Wrong assumption in calculus: Original: 'The derivative of  $x^2$  is 2x.' Misleading: 'The derivative of  $x^2$  is x.' Incorrect triangle property: Original: 'In this right triangle, the hypotenuse is 10.' Misleading: 'In this right triangle, the hypotenuse is 8.' 

Wrong direction in vector problems: Original: 'The vector points in the positive x-direction.' Misleading: 'The vector points in the negative x-direction. 

C.3 PROMPTS FOR RESPONSE GENERATION

We follow MathVista (Lu et al., 2023) to prepend an instructional prompt header into each question. The prompt can be found in Table 4.

### D MORE EXPERIMENTAL RESULTS

In this section, we provide more experimental results. 

**Results on different question types and answer types.** We first discuss the performance of LMMs on different question types: multi-choice and free-form, and answer types: text, integer, and float (since the number of list-type questions is too small, we ignore them here). The results are shown in Figure 8. We can find that the open-source models perform very poorly on free-form problems. Since free-form problems need accurate answers, the computational ability of open-source models can not support them in obtaining accurate final answers. Compared with open-source models, closed-source models show a better balance of accuracy between multi-choice problems and free-form problems.



$\Delta$	-8.40	-0.48	-12.03	-4.46	-21.51	-6.70	+0.42	-3.20	-7.97	+0.42	-12.18	+2.70	-11.11
						Gemini	Pro 1.5						
Δ	-3.70	-6.20	-8.86	+0.00	-5.38	+0.00	-1.66	-1.66	-7.81	-6.27	-0.89	-2.02	-2.08

Table 7: Performance Delta of using spurious caption as extra text on MathVista. ALL: overall accuracy. Task types: FQA: figure question answering, GPS: geometry problem solving, MWP: math word problem, TQA: textbook question answering, VQA: visual question answering. Mathematical reasoning types: ALG: algebraic reasoning, ARI: arithmetic reasoning, GEO: geometry reasoning, LOG: logical reasoning, NUM: numeric commonsense, SCI: scientific reasoning, STA: statistical reasoning. Positive changes are in blue and negative changes in red.

Results on MathVista with spurious captions. We provide the results on MathVista under the setting of spurious captions. The results are shown in Table 7. Similar to experiments done on EEE-Bench, adding spurious captions into text will significantly degrade LMMs' performance.

Examples of response from LMMs. In Figure 41 and Figure 42, we provide qualitative examples of responses for LMMs for reference.

Wrong responses from GPT-40 augmented with captions. We discuss examples of wrong responses from
 GPT-40 with augmented captions. Figure 29 and Figure 30 show examples. We found that these errors stem from
 incorrectly generated captions, which aligns with the concept of LMM laziness.

# E MODEL AND HYPERPARAMETER

The release time and source of open-source and closed-source models can be found in Table 8. For closed-sourced models, we access them with APIs and adopt the generation scheme shown in Table 5. and then run the inference with CPUs, which typically completes within several hours. For all open-source models, we utilize a cluster with 8 NVIDIA 40GB A100 GPUs to run the inference, and we follow the hyper-parameter settings specified in Table 6.

# F MORE ABOUT EEE-BENCH

In this section, we provide more examples of images of EEE-Bench. Figure 9 presents images from Digital Logic Circuits and Microprocessor Design. Figure 10 presents images from Circuit Theory and Network Analysis. Figure 11 presents images from Analog Circuits. Figure 12 presents images from Power Electronics and Power Systems. Figure 13 presents images from Signals and Systems. Figure 14 presents images from Communication Systems. Figure 15 presents images from Control Systems. Figure 16 presents images from Electronic Devices. Figure 17 presents images from Electrical Machines. Figure 18 presents images from Electromagnetics. EEE-Bench covers a wide range of images and thus can comprehensively evaluate the visual reasoning abilities of LMMs.

Table 8:	The Release	<b>Time and Model</b>	Source of LMMs	Used in EEE-Bench.
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Model	Release Time	Source				
GPT-40	2024-05	https://gpt4o.ai/				
GPT-4V	2024-04	https://openai.com/index/ gpt-4v-system-card/				
GPT-4o-mini	2024-07	https://openai.com/index/gpt-4o-mini-advancing-cost- efficient-intelligence				
Gemini 1.5 Pro	2024-05	https://deepmind.google/technologies, gemini/pro/				
Gemini 1.5 Flash	2024-05	https://deepmind.google/technologies, gemini/flash/				
Qwen-VL-Plus	2023-11	https://help.aliyun.com/zh/ dashscope/developer-reference/ vl-plus-quick-start				
Qwen-VL-Max	2024-01	https://help.aliyun.com/zh/ dashscope/developer-reference/ vl-plus-quick-start				
LLaVA-1.6-7B	2024-03	https://huggingface.co/liuhaotian/ llava-v1.6-mistral-7b				
LLaVA-1.6-13B	2024-03	https://huggingface.co/liuhaotian/ llava-v1.6-vicuna-13b				
SPHINX-Plus	2023-11	https://huggingface.co/Alpha-VLLM/ LLaMA2-Accessory/tree/main/finetune/ mm/SPHINX/SPHINX-v2-1k				
MiniCPM-V-2.6	2024-08	https://github.com/OpenBMB/MiniCPM-V				
DeepSeek-VL-7B	2024-03	https://huggingface.co/deepseek-ai/ deepseek-vl-7b-chat				
Phi3-Vision-4.2B	2024-05	https://huggingface.co/microsoft/ Phi-3-vision-128k-instruct				
InternVL2-26B	2024-07	https://huggingface.co/OpenGVLab/ InternVL2-26B				
InternLM-XComposer2.5-7B	2024-07	https://huggingface.co/internlm/ internlm-xcomposer2d5-7b				
GLM-4V-9B	2024-06	https://huggingface.co/THUDM/ glm-4v-9b				

Table 10: Required Abilities for LMM among EEE Subjects

1139		
1140	Subject	Required LMM Abilities
1141	(1) Digital Logic Circuits and	Solving problems in this domain requires models to deeply understand in-
1142	Microprocessor Design	tricate logic relationships in digital circuits and reason effectively. While
1143		these problems demand strong logical structuring and timing analysis ca-
1144		mathematical computations. The ability to recognize logic patterns and
1145		reason through circuit operations is essential.
1147	(2) Circuit Theory and Network	I MMs tackling problems in this subject require extensive computational
1148	Analysis	processing abilities. The models must be proficient in solving complex
1149		equations and applying numerical methods to analyze and interpret circuit
1150		behaviors under varying conditions. Although less complex in terms of
1151		logic, these problems require strong numerical and computational skills to
1152		manage transferit and steady-state responses.
1153	(3) Analog Circuits	For analog circuits, LMMs must handle complex visual contexts, includ-
1154		ing intricate circuit diagrams. These problems demand both sophisticated
1155		vision recognition abilities to interpret circuit structures and strong com-
1156		putational skills to predict continuous signal benavior. Advanced mathe-
1157		matical tools, such as Laplace transforms and frequency domain analysis,
1158		are required for solving circuit dynamics and performance analysis.
1159		Continued on next page

Subject	Required LMM Abilities
(4) Power Electronics and Power Systems	LMMs solving power electronics and power systems problems must n age large-scale computational tasks related to energy conversion, grid namics, and efficiency optimization. Although the visual elements m not be as complex as other subjects, the computational effort needed modeling and simulating power systems is significant. Strong numer capabilities and reasoning about energy flow are crucial.
(5) Signals and Systems	This domain requires LMMs to process and analyze signals in both and frequency domains. Vision recognition skills are needed to unders the visual representations of signals, such as waveforms and spectrogra while computational tools like Fourier and Laplace transforms mus applied to analyze system responses. The models need to handle symbolic reasoning and numerical calculations.
(6) Communication Systems	Although the visual information in communication systems tends to straightforward, solving these problems demands considerable comp tional effort. LMMs must decode and simulate communication protoc analyze noise, and optimize transmission systems. Numerical accu and simulation capabilities are key for optimizing communication co- nels and analyzing signal integrity.
(7) Control Systems	LMMs addressing control system problems must excel in both reasonand computation. Feedback systems require sophisticated reasonin design and stabilize control loops, while mathematical modeling and a ulation of dynamic systems call for strong computational abilities. C plex visual representations of system dynamics, such as block diagra require models to recognize system structures and respond according
(8) Electronic Devices	In this subject, LMMs must understand the physical principles of semi- ductor devices, but the problems primarily involve numerical computa to predict device behaviors. Visual contexts, such as device schema are generally simple, but the computational tasks can be intensive, rec ing models to handle material properties and electrical characteristics high precision.
(9) Electrical Machines	Problems in this domain involve electromechanical energy converse and LMMs must reason about mechanical and electrical interactions. visual complexity is moderate, but models must be proficient in nume simulations to predict machine performance under different conditi Computational tools are essential for solving mechanical equations analyzing energy transfer processes.
(10) Electromagnetics	LMMs need to possess strong reasoning skills to interpret complex vi contexts like field distributions and wave propagation diagrams. Addit ally, these problems demand high computational power to solve Maxw equations and simulate electromagnetic fields. Numerical accuracy proficiency in solving partial differential equations are key to success addressing challenges in this domain.

To better help readers understand the key points of these ten subjects, we provide a detailed introduction for each in this section. Further information on each subject is available in Table 9.

# H REQUIRED ABILITY FOR LMMS TO SOLVE EEE PROBLEMS

In this section, we discuss the characteristics of each subject's problems and the required ability for LMMs to solve
 them. The discussion can be found in Table 10. Some examples of problems and detailed solutions in EEE-Bench are shown in Figure 20, Figure 21, Figure 22, Figure 23, Figure 24.



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### Ι MORE EXAMPLES OF ERROR ANALYSIS

In this section, we give more examples of error analysis. Figure 25 and Figure 26 are examples of image perception errors. Figure 27 and Figure 28 are examples of reasoning errors.

### MORE EXAMPLES OF LMM LAZINESS J

1271 In this section, we provide more examples of the laziness phenomenon of existing LMMs. Figure 31, Figure 32, 1272 Figure 33, Figure 34, Figure 35, Figure 36, Figure 37 and Figure 38 show examples of LMM laziness phenomenon 1273 on EEE-Bench. Figure 39 and Figure 40 show examples of LMM laziness phenomenon on MathVista. We can 1274 find that when there is (misleading) information for problem-solving in text, the LMMs will not try to read the relevant information in the images, even if this information is spurious. Consequently, LMMs generate wrong 1275 answers with this spurious information.



Figure 12: Examples of images from Power Electronics and Power Systems









Figure 18: Examples of images from Electromagnetics

Subject	Description and Key Knowledge
(1) Digital Logic Circuits and Microprocessor Design	Focuses on boolean logic, logic gates design, and the sequential c fundamental to digital systems. Key challenges include micropro architecture analysis, timing issues, and peripheral interfacing, requ deep understanding of logic operations and system integration.
(2) Circuit Theory and Network Analysis	Involves detailed study of Ohm's and Kirchhoff's laws, network rems, and electrical components. Emphasizes solving complex net through techniques like mesh and nodal analysis, with problems off volving around transient and steady-state behaviors in electrical circ
(3) Analog Circuits	Covers operational amplifiers, filters, and oscillators, focusing on the sign and analysis of circuits for continuous signal processing. Chall include designing robust power amplifiers and ensuring accurate rest analysis in varying operational conditions.
(4) Power Electronics and Power Systems	Examines electrical power conversion and control using semiconor devices. Key areas include designing efficient converters and inv and managing complex power systems with an emphasis on optim grid dynamics and energy distribution.
(5) Signals and Systems	Deals with the representation and analysis of signals and the behaves systems, employing tools like Fourier and Laplace transforms. Chall include analyzing both time-domain and frequency-domain data to a stand system properties and behaviors.
(6) Communication Systems	Focuses on techniques for efficient signal transmission and receptic volves studying modulation schemes, coding techniques, and noise sis with problems often related to designing and optimizing comm tion links and networks for reliability and performance.
(7) Control Systems	Addresses the design and analysis of dynamic systems using feed Involves stability analysis and controller design, with practical chall in tuning controllers like PID for desired system responses and en- long-term stability and reliability.
(8) Electronic Devices	Explores semiconductor physics and the application of devices like of and transistors. Problems focus on device operation under differen ditions and the integration of special purpose devices such as LEE photodetectors in practical applications.
(9) Electrical Machines	Studies the principles of operation and design of electric machines st transformers and motors. Key challenges include analyzing perform designing for efficiency, and understanding the electromechanical in tions in different operating conditions.
(10) Electromagnetics	Explores Maxwell's equations and their applications in electroma field theory and wave propagation. Challenges include designing mission lines, waveguides, and antennas, and ensuring electroma compatibility in various applications.



1624 1625 MM MA 1629 1631 w 1632 1633 1634 1635 1636 w 1637 Subject: Analog Circuits 1639 **Question:** The  $\frac{V_{OUT}}{V_{IN}}$  of the circuit shown in figure is ( ). 1640 1641 A:  $-\frac{R_4}{R_3}$  B:  $\frac{R_4}{R_2}$  C:  $1 + \frac{R_4}{R_2}$  D:  $1 - \frac{R_4}{R_2}$ 1642 1643 1644 Solution: Here,  $A_1$  is an inverting amplifier and  $A_2$  is a non-inverting amplifier. 1645  $V_{01} = \frac{-R_2}{R_1} V_{in}, V_{02} = \left(1 + \frac{R_2}{R_1}\right) V_{in}$ 1646 1647 1648 Also,  $A_3$  is an inverting summing amplifier,  $V_{out} = \frac{-R_4}{R_3} V_{01} + \frac{-R_4}{R_3} V_{02} = \frac{-R_4}{R_3} \left[ \frac{R_2}{R_1} V_{in} + \left( 1 + \frac{R_2}{R_1} \right) V_{in} \right]$ 1650 1651 1652  $V_{out} = \frac{-R_4}{R_2} V_{in}$ 1653 1654 Gain, 1655  $\frac{V_{out}}{V_{in}} = \frac{-R_4}{R_3}$ 1656 1657 1658 Answer: A 1659 OX[0] x[0] O1660 OX[1]1661 x[3]1662 OX[2] x[1663 1664 OX[3] x[4]OX[4]x[2] C 1666 1667 OX[5] x[5]-1 Subject: Signals and Systems 1669 Question: Consider a six-point decimation-in-time Fast Fourier Transform (FFT) algorithm, for which the 1670 signal-flow graph corresponding to X[1] is shown in the figure. Let  $W_6 = \exp\left(-\frac{j2\pi}{6}\right)$ . In the figure, what Signal-now graph corresponding to  $X_{[1]}$  is snown in the figure. Let  $W_6 = \exp\left(-\frac{x_6}{6}\right)$ . In the figure, we should be the values of the coefficients  $a_1, a_2, a_3$  in terms of  $W_6$  so that  $X_{[1]}$  is obtained correctly?  $A: a_1 = -1, a_2 = W_6, a_3 = W_6^2 \quad B: a_1 = 1, a_2 = W_6^2, a_3 = W_6$   $C: a_1 = 1, a_2 = W_6, a_3 = W_6^2 \quad D: a_1 = -1, a_2 = W_6^2, a_3 = W_6$  **Solution:**  $X(k) = \sum_{n=0}^{N-1} x(n)e^{-j\frac{2\pi}{N}kn}$ .  $X(1) = \sum_{n=0}^5 x(n)W_6^n = x(0) + x(1)W_6 + x(2)W_6^2 + x(3)W_6^3 + x(4)W_6^4 + x(5)W_6^5 \dots (i)$ From the given flow graph, we have  $X(k) = [x(0) - x(3)]a_1 + [x(1) - x(4)]a_2 + [x(2) - x(5)]a_3 \dots (ii)$ . By comparing equations (i) and (ii), we get  $a_1 = 1, a_2 = W_6, a_3 = W_6^2$ . 1671 1672 1673 1674 1675 1676 1677 1678 Answer: C 1679 Figure 21: Examples of problems in EEE-Bench. 1681















Figure 28: Reasoning Error examples of the response from GPT-40. The error part in response is marked as red color



#### Caption context: Image caption context: 2093

The diagram consists of four subplots labeled A, B, C, and D. Each subplot represents a graph of current versus voltage, 2094 specifically for a transistor, likely a MOSFET or JFET, based on the axes labels. Here is a detailed description of each 2095 subplot:

2096 Subplot A: - **Axes**: - Horizontal axis: V_{GS} (Gate-Source Voltage) - Vertical axis: I_D (Drain Current) - **Graph**: -The curve starts in the third quadrant and moves into the first quadrant, indicating a negative  $V_{GS}$  initially, with  $I_D$  increasing 2097 as  $V_{GS}$  becomes positive. - The curve is nonlinear, showing a gradual increase in  $I_D$  with increasing  $V_{GS}$ .

Subplot B: - **Axes**: - Horizontal axis: VGS (Gate-Source Voltage) - Vertical axis: ID (Drain Current) - **Graph**: -2099 The curve starts near the origin and sharply rises in the first quadrant, indicating a rapid increase in  $I_D$  with a small increase 2100 in  $V_{GS}$ . - The curve is steep, suggesting a strong dependency of  $I_D$  on  $V_{GS}$ .

2101 Subplot C: - **Axes**: - Horizontal axis: V_{GS} (Gate-Source Voltage) - Vertical axis: I_D (Drain Current) - **Graph**: -The curve starts at the origin and rises steeply in the first quadrant, similar to subplot B, but with a more pronounced initial 2102 slope. - This indicates a very sensitive response of  $I_D$  to changes in  $V_{GS}$ . 2103

Subplot D: - **Axes**: - Horizontal axis: VGS (Gate-Source Voltage) - Vertical axis: ID (Drain Current) - **Graph**: -2104 The curve starts in the third quadrant and moves into the first quadrant, similar to subplot A, but with a more pronounced 2105 initial curvature. - The curve shows a nonlinear increase in  $I_D$  as  $V_{GS}$  becomes positive, indicating a threshold behavior.

2106 General Observations: - Each subplot represents a different characteristic curve of a transistor, likely showing different modes of operation or types of transistors. - The  $V_{GS}$  and  $I_D$  relationship is crucial for understanding the behavior of the 2107 transistor in different configurations or biasing conditions. - The curves suggest different levels of sensitivity and threshold 2108 behavior, which are important for designing and analyzing circuits involving these components. 2109

- Question: The graph that correctly describes the transfer characteristics of an enhancement-mode NMOSFET (assuming 2110 current always flows into the drain as the positive direction) is ().
- 2111 A. graph A B. graph B C. graph C D. graph D
- Response w/o caption: The correct graph that describes the transfer characteristics of an enhancement-mode NMOSFET is 2112 graph C. 2113
- C Response w/ caption: The graph that correctly describes the transfer characteristics of an enhancement-mode NMOSFET 2114 is **graph B* 2115

In an enhancement-mode NMOSFET, the drain current  $I_D$  starts to increase significantly only after the gate-source voltage 2116  $V_{GS}$  exceeds a certain threshold voltage. This behavior is depicted in graph B, where  $I_D$  sharply rises in the first quadrant 2117 as  $V_{GS}$  increases.

- Caption context: Image caption context: 2122

The diagram depicts an electrical circuit with the following components and connections: 2123

1. **AC Source**: - Represented by the symbol for alternating current (AC) on the left side of the diagram. - It provides 2124 the input power to the circuit.

2125 2. **Ammeter (A)**: - Connected in series with the primary coil of a transformer. - Measures the current flowing through 2126 the primary side.

3. **Transformer**: - Consists of two coils: the primary coil (connected to the AC source and ammeter) and the secondary 2127 coil. - The primary coil is on the left, and the secondary coil is on the right. 2128

4. **Resistor (R)**: - Connected in series with the secondary coil of the transformer. - Represents a load or impedance in 2129 the circuit.

2130 5. **Lamp L1**: - Connected in parallel with the resistor (R). - Indicates the presence of current through the secondary 2131 circuit.

6. **Switch (S)**: - Connected in series with another lamp (L2). - Controls the current flow to lamp L2. 2132

- 7. **Lamp L2**: Connected in series with the switch (S). Illuminates when the switch is closed, indicating current flow 2133 through this path. 2134
- 8. **Connections**: The secondary coil of the transformer is connected to both the resistor (R) and lamp L1 in parallel. -2135

The switch (S) and lamp L2 are connected in series, forming a parallel branch with the resistor and lamp L1.

2136 This setup can be used to study the behavior of AC circuits, the effect of transformers, and the operation of parallel and series components in electrical systems. 2137

Question: As shown in the figure, the primary coil is input with a stable AC voltage, and switch S is in the open state. At a 2138 certain moment, bulb  $L_1$  becomes slightly dimmer. The possible reason could be:

- 2139 A. The input voltage increased B. Switch S was closed
- 2140 C. The resistor  $\boldsymbol{R}$  short-circuited D. The ammeter experienced an open circuit
- **Response w/o caption:** The possible reason bulb  $L_1$  becomes slightly dimmer is: B. Switch S was closed 2141

When switch S is closed, current can flow through bulb  $L_2$ , reducing the current through  $L_1$  and making it dimmer. **Re**-2142

sponse w/ caption: The possible reason for bulb  $L_1$  becoming slightly dimmer is: C. The resistor R short-circuited 2143 If the resistor R short-circuits, it would reduce the total resistance in the parallel branch, causing more current to flow 2144 through the shorted path and less through  $L_1$ , making it dimmer.

2145 Figure 29: Examples of LMM errors with captions in EEE-Bench o fGPT-40. We mark the errors in response with red color



# 2151 caption context: Image caption context:

- The diagram represents a periodic signal  $x_3(t)$  with a period of 10 units. Here is a detailed description of the waveform:
- 2153 1. **Signal Type**: The signal is a square wave.
- 2. **Periodicity**: The function is periodic with a period T = 10. This is indicated by the equation  $x_3(t) = x_3(t+10)$ .

3. **Amplitude Levels**: The waveform alternates between two amplitude levels: -+1 - -1

4. **Time Intervals**: - The signal is at +1 from t = 0 to t = 1. - The signal drops to -1 from t = 1 to t = 3. - The signal returns to 0 from t = 3 to t = 10.

5. **Repetition**: This pattern repeats every 10 units along the time axis, both to the left and right, as indicated by the ellipses (...).

2159 6. **Key Points**: - At t = 0, the signal jumps to +1. - At t = 1, the signal drops to -1. - At t = 3, the signal returns to 0. - At t = 10, the pattern repeats.

This description captures all the essential features of the waveform, allowing for analysis or reconstruction without the visual diagram.

**Question:** Determine the Fourier series coefficient  $c_0$  for x3(t) shown in figure.  $c_0 = ()$ 

**2163 Response w/o caption:** To find the Fourier series coefficient  $c_0$ , which represents the average value of the function over one period, we need to integrate the function over one period and divide by the period length.

Given the periodic function  $x_3(t)$  with period T = 10, we can calculate  $c_0$  as follows:

$$c_0 = \frac{1}{T} \int_0^T x_3(t) \, dt$$

From the graph, the function  $x_3(t)$  is:

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- 1 from t = 0 to t = 1 - -1 from t = 2 to t = 3 - 0 elsewhere in the period Now, calculate the integral:

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$$c_0 = \frac{1}{10} \left( \int_0^1 1 \, dt + \int_2^3 (-1) \, dt \right)$$

$$c_0 = \frac{10}{10} \left( [t]_0^2 + [-t]_2^2 \right)$$

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2176 
$$c_0 = \frac{1}{10} \left( (1-0) + (-(3) - (-(2))) \right)$$

2177 2178  $c_0 = \frac{1}{10} (1-1)$ 

$$c_0 = \frac{1}{10} \times 0$$

2180 10  
2181 
$$c_0 = 0.0$$

2182 Thus, the Fourier series coefficient  $c_0$  is 0.0.

**Response w/ spurious caption:** To find the Fourier series coefficient  $c_0$  for the signal  $x_3(t)$ , we need to calculate the average value of the signal over one period. The coefficient  $c_0$  is given by:

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$$c_0 = \frac{1}{T} \int_0^T x_3(t) dt$$

Given the period T = 10, we can break the integral into segments based on the time intervals provided: 1. From t = 0 to t = 1,  $x_3(t) = 1$ . 2. From t = 1 to t = 3,  $x_3(t) = -1$ . 3. From t = 3 to t = 10,  $x_3(t) = 0$ . Now, calculate the integral:  $c_0 = \frac{1}{10} \left( \int_0^1 1 \, dt + \int_1^3 (-1) \, dt + \int_0^{10} 0 \, dt \right)$ 

Thus, the Fourier series coefficient  $c_0$  is -0.1.

Figure 30: Examples of LMM errors with *captions* in EEE-Bench o f GPT-40. We mark the errors in response with red color







### 2327 Spurious context: Image caption context:

- The diagram represents a periodic rectangular pulse signal  $x_1(t)$  with the following characteristics:
- 1. Signal Description: The signal is periodic with a period of 20 units of time. The mathematical expression for the signal is  $x_1(t) = x_1(t+20)$ , indicating its periodic nature.
- 2. Pulse Characteristics: Each pulse has an amplitude of 2. The pulse width is 2 units of time, starting at integer multiples
   of 5 (e.g., 0, 5, 10, etc.).
- 2332 3. Time Axis: The horizontal axis represents time t. The vertical axis represents the amplitude of the signal.

4. Pulse Position: - The first pulse starts at t = 0 and ends at t = 2. - The second pulse starts at t = 5 and ends at t = 7. - This pattern continues indefinitely in both directions, as indicated by the ellipses (...).

- 5. Signal Behavior: The signal is zero for all time intervals except during the pulse width of 2 units at each period.
   This description provides a complete understanding of the periodic rectangular pulse signal depicted in the diagram, suitable
- for analysis in various electrical and electronics engineering contexts.
- **Question:**Determine the Fourier series coefficients  $a_0$  for  $x_1(t)$  shown in figure.  $a_0=()$ .

**Response w/o spurious caption:** To find the Fourier series coefficient  $a_0$  for the periodic function  $x_1(t)$ , we need to calculate the average value of the function over one period.

The function  $x_1(t)$  is a periodic square wave with a period T = 10. It has a value of 1 from t = 0 to t = 1 and 0 from t = 1 to t = 10.

**2341** The formula for  $a_0$  is:

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$$a_0 = \frac{1}{T} \int_0^T x_1(t) \, dt$$

Substituting the given values:

$$a_0 = \frac{1}{10} \left( \int_0^1 1 \, dt + \int_1^{10} 0 \, dt \right)$$
$$a_0 = \frac{1}{10} \left( [t]_0^1 + 0 \right)$$
$$a_0 = \frac{1}{10} (1 - 0) = 0.1$$

Thus, the Fourier series coefficient  $a_0$  is 0.1.

**Response w/o spurious caption:** To determine the Fourier series coefficient  $a_0$  for the periodic rectangular pulse signal  $x_1(t)$ , we need to calculate the average value of the signal over one period. The formula for  $a_0$  is:

$$a_0 = \frac{1}{T} \int_0^T x_1(t) \, dt$$

where T is the period of the signal. For this signal, T = 20. The signal  $x_1(t)$  has an amplitude of 2 for a duration of 2 units of time in each period and is zero otherwise. Therefore, the integral over one period is:

$$\int_{0}^{20} x_1(t) dt = \int_{0}^{2} 2 dt + \int_{5}^{7} 2 dt + \int_{10}^{12} 2 dt + \int_{15}^{17} 2 dt$$

Calculating each integral:

$$\int_{0}^{2} 2 \, dt = 2 \times 2 = 4, \ \int_{5}^{7} 2 \, dt = 2 \times 2 = 4$$
$$\int_{10}^{12} 2 \, dt = 2 \times 2 = 4, \ \int_{15}^{17} 2 \, dt = 2 \times 2 = 4$$

 $a_0 = \frac{1}{20} \times 16 = 0.8$ 

Adding these, the total integral over one period is: 4 + 4 + 4 = 16. Now, calculate  $a_0$ :

Thus, the Fourier series coefficient  $a_0$  is 0.8.

Figure 33: Examples of LMM laziness in EEE-Bench. We mark the *spurious text* in the caption and error in response with red color



- 1. Inputs and Outputs: The input to the system is denoted as X(s). The output of the system is denoted as Y(s).
- 2. Summing Junctions: There are three summing junctions in the diagram. The first summing junction has three inputs:
- X(s) with a negative sign and a feedback path with a positive sign. The second summing junction has two inputs, all with negative signs.
- 2392 3. Paths and Connections: The output of the first summing junction is connected to a path labeled N(s). This path leads to the second summing junction.
- 4. Delay Elements: There is one delay element in the diagram, represented by a block labeled  $s^{-1}$ . The delay element is connected in parallel with the output of the first summing junction.
- 5. Feedback and Feedforward Paths: The output of the delay element is fed back to the first summing junction with a gain of K. - The output of the delay element is connected to the second summing junction with a gain of 3. - The output of the second summing junction is also connected to the second summing junction with a gain of 2.
- 6. Gains: The feedback path from the output of the delay element to the first summing junction has a gain of K. The feedforward path from the output of the delay element to the second summing junction has a gain of 3. The feedforward path from the output of the second summing junction has a gain of 2.
- This block diagram represents a continuous-time system with feedback and feedforward paths, incorporating a delay element and gains, which can be analyzed using Laplace transform techniques to determine the system's behavior and response.
- **2402** Question: If the system is stable when a < K < b, then a + b = ().
- **Response w/o spurious caption:** To determine the stability of the system, we need to find the characteristic equation of the closed-loop transfer function. The system has two delay elements, each represented by  $z^{-1}$ .
- The transfer function M(z) can be derived from the block diagram:
- 1. The forward path gain is 1. 2. The feedback path includes two delay elements and a gain *K*.
- The characteristic equation for the closed-loop system is:

$$1 + Kz^{-2} = 0$$

Solving for z, we get:

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$$Kz^{-2} = -1, z^2 = -K$$

For stability, the poles of the system must lie inside the unit circle in the z-plane. This means the magnitude of z must be less than 1: |z| < 1. Substituting  $z^2 = -K$ , we have:

$$|-K| < 1, K < 1$$

Additionally, since  $z^2 = -K$ , K must be positive for the system to have real poles: K > 0 Thus, the system is stable when 0 < K < 1. Therefore, a = 0 and b = 1, so:

$$a + b = 0 + 1 = 1.0$$

The final value is 1.0.

**Response w/ spurious caption:** To determine the stability of the system, we need to analyze the characteristic equation derived from the block diagram. The system is stable if all poles of the transfer function have negative real parts. Given the block diagram, the characteristic equation can be derived from the feedback loop. The transfer function H(z) can be expressed as:

$$H(z) = \frac{Y(z)}{X(z)} = \frac{M(z)}{1 + M(z) \cdot G(z)}$$

where M(z) is the forward path transfer function and G(z) is the feedback path transfer function. From the diagram: - The forward path M(z) includes the two delay elements, so  $M(z) = \frac{1}{z^2}$ . - The feedback path G(z)includes the gain K and the delay elements, so  $G(z) = K \cdot \frac{1}{z^2}$ . The characteristic equation is:

$$1 + M(z) \cdot G(z) = 1 + \frac{1}{z^2} \cdot K \cdot \frac{1}{z^2} = 1 + \frac{K}{z^4} = 0$$

This simplifies to:  $z^4 + K = 0$ . For stability, the roots of this equation must lie inside the unit circle in the z-plane. The roots are:  $z = \sqrt[4]{-K}$ 

For the system to be stable, the magnitude of z must be less than 1: 
$$|\sqrt[4]{-K}| < 1$$
 This implies:  $|K| < 1$  Thus, the system is stable when  $-1 < K < 1$ . Therefore,  $a = -1$  and  $b = 1$ , so  $a + b = 0$ . The final value is 0.0.

Figure 34: Examples of LMM laziness in EEE-Bench. We mark the *spurious text* in the caption and error in response with red color



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Spurious context: Image caption context: 2472

The diagram appears to represent a section of a simple electrical circuit involving basic resistive components. Here is a 2473 detailed description of the components and parameters: 2474

1. Rectangular Block: - The main component is a rectangular block, which could represent a resistor or a non-conductive 2475 barrier. 2. Magnetic Flux Density (B): - Arrows pointing into the bottom surface of the block indicate the direction of the magnetic flux density (B), suggesting that the block is outside of any magnetic field influence. 3. Electric Current (I): - An 2476 arrow labeled I is shown outside the block, indicating the direction of electric current flow around the block, not through 2477 it. 4. Electric Displacement Field (D): - Arrows labeled D are shown exiting the right side of the block, indicating the 2478 direction of the electric displacement field. This suggests the absence of an electric field within the block. 5. Voltage (V): 2479 - A curly bracket on the left side of the block is labeled V, indicating the potential difference or voltage along the side of 2480 the block. 6. Surface (S): - The bottom surface of the block is labeled S, which could represent the area unrelated to the 2481 magnetic flux density.

This diagram likely represents a scenario involving basic electrical principles, such as a simple resistor circuit, where electric 2482 fields and currents are minimally interacting with magnetic fields. The parameters **B**, **D**, *I*, *V*, and *S* are used to analyze 2483 the basic electrical behavior of the system. 2484

- **Question:** A conductor carrying a current I has a thickness D and a cross-sectional area S. It is placed in a uniform 2485 magnetic field with a magnetic flux density B, where the magnetic field direction is perpendicular to the side surface of the 2486 conductor, as shown in the figure. The potential difference between the top and bottom surfaces of the conductor is measured to be V. The Hall coefficient of this conductor is: Choices: (A)  $\frac{VDS}{IB}$  (B)  $\frac{IBV}{DS}$  (C)  $\frac{VS}{IBD}$  (D)  $\frac{IVS}{BD}$  (E)  $\frac{VD}{IB}$ 2487
- 2488

**Response w/o spurious caption:** The Hall coefficient  $R_H$  is given by the formula:  $R_H = \frac{VD}{IB}$  Thus, the correct option is: 2489 (E)  $\frac{VD}{IB}$ 2490

**Response w/ spurious caption:** The Hall coefficient  $(R_H)$  is given by the formula:  $R_H = \frac{V}{IBD}$  This formula relates the 2491 Hall voltage (V), current (I), magnetic flux density (B), and thickness (D) of the conductor. 2492

Therefore, the correct choice is: (C)  $\frac{VS}{IBD}$ 2493

Figure 35: Examples of LMM laziness in EEE-Bench. We mark the spurious text in the caption and error in response with red color



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2563	$318 \Psi \downarrow^{\mu_1} \Pi_{\mu_2}$
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2566	Sourieus context. Image contien context.
2567	<b>Spurious context:</b> Infage capiton context: The diagram represents an electrical circuit with the following components and connections:
2568	1. Ammeter (A): - Positioned at the end of the circuit Measures the voltage across the circuit.
2560	2. Transformer: - Consists of two coils (primary and secondary) without a core symbol between them The primary coil is
2505	connected in parallel with the ammeter The secondary coil is connected to the rest of the circuit.
2570	3. Voltmeter (V): - Connected in series with the secondary coil of the transformer Measures the current through the
2571	secondary coil. 4. Design $D_{i}$ . Connected in action with the voltmeter. Dort of the load on the minimum side of the transformer
2012	4. Resistor $R_1$ : - Connected in series with the volumeter Part of the load of the primary side of the transformer. 5. Switch (S): - Connected in parallel with resistor $R_{0}$ - Controls the disconnection of $R_{0}$ from the circuit
2010	6. Resistor $R_2$ : - Connected in parallel with the switch When the switch is closed, $R_2$ is removed from the circuit.
2574	**Connections**: - The primary side of the transformer is connected in parallel with the ammeter The secondary side
2575	of the transformer is connected in series to the voltmeter and resistor $R_1$ The switch S and resistor $R_2$ are connected in
2576	parallel, forming a series branch with $R_1$ when the switch is closed.
2577	This setup can be used to measure the voltage and current in a transformer circuit, and to analyze the effects of removing or adding a series lead (resister $P_{\rm eff}$ ) on the girapit
2578	<b>Ouestion:</b> In the circuit shown in figure an ideal transformer has its primary coil connected to a high voltage and its
2579	secondary coil connected to a load, with the line resistance being negligible. When S is initially closed and $R_1 = R_2$ , and
2580	then S is opened, the AC voltage reading U, AC current reading I, and power $P_1$ on the load $R_1$ will
2581	A. U increases, I increases, $P_1$ increases
2582	B. U remains unchanged, I decreases, $P_1$ increases
2583	C. U decreases, I decreases, $P_1$ decreases D U remains unchanged I decreases $P_1$ remains unchanged
2584	<b>Response w/o spurious caption:</b> When the switch S is initially closed, the total resistance in the secondary circuit is
2585	$R_1 + R_2$ . When S is opened, the resistance becomes just $R_1$ .
2586	Since $R_1 = R_2$ , opening the switch doubles the resistance in the secondary circuit.
2587	1. **Voltage $U$ :** The voltage across the load $R_1$ remains unchanged because the transformer maintains the same voltage
2588	ratio regardless of the load.
2589	2. **Power $P_1$ :** The power $P_1 = U^2/R_1$ remains unchanged because the voltage across $R_1$ remains the same and $R_1$
2590	itself does not change.
2591	Therefore, the correct answer is:
2592	D. $U$ remains unchanged, $I$ decreases, $P_1$ remains unchanged
2593	<b>Response w/ spurious caption:</b> In the given circuit, when the switch S is initially closed, resistors $R_1$ and $R_2$ are in
2594	parallel, ellectively reducing the total resistance on the secondary side. when S is opened, $R_2$ is removed, leaving only $R_1$ in the circuit, which increases the total resistance
2595	1. **Voltage U:** The voltage across the secondary coil remains unchanged because the transformer maintains a constant
2596	voltage ratio between the primary and secondary coils.
2597	2. **Current I:** With the increase in resistance (since $R_2$ is removed), the current through the circuit decreases.
2598	3. **Power $P_1$ :** Power is given by $P = I^2 R$ . Since the current decreases and the resistance remains constant at $R_1$ , the
2599	power P ₁ decreases.
2600	C U decreases I decreases P ₁ decreases
2601	Eigune 27. Examples of LMM loginous in EEE Danch. We much the much in the anti-
2602	rigure 57: Examples of Livivi laziness in EEE-Bench. we mark the <i>spurious text</i> in the caption and error in response with red color
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69 70						
70		oval bead	ds	\$2/kilogram		
		rectangu	lar beads	\$3/kilogram		
71		star-shar	heads	\$2/kilogram		
72		Star Shap		¢2/kilogram		
74		spherical	beads	\$2/kilogram		
75		heart-sha	aped beads	\$3/kilogram		
76		square b	eads	\$2/kilogram		
77		a l		¢2/talogram		
78 70		flower-sh	aped beads	\$2/kilogram		
80	<b>Spurious context:</b> Image caption co	ontext:	ands along with their	r prices per kilog	ram. The table has two columns: the	
81	first column lists the bead shapes, an	d the second	l column lists the cor	responding prices	The table is organized as follows:	
82	1. Oval beads - priced at \$3 per kilo	gram. 2. Re	ctangular beads - pri	ced at \$2 per kild	ogram. 3. Star-shaped beads - priced	
33	at \$3 per kilogram. 4. Spherical bea	ads - priced a ram 7 Flow	at \$3 per kilogram. 3	b. Heart-shaped t riced at \$3 per kil	ogram	
4	The table is presented with a light b	lue backgro	und, and each row al	ternates in a slig	htly darker shade of blue for clarity.	
5	This table can be used for calculation	ns involving	the cost of purchasin	g different types	of beads by weight.	
7	(Unit: \$)	lograms of o	val beads and 5 kilog	grams of star-shap	bed beads. How much will he spend?	
	<b>Response w/o spurious caption:</b> C	hase wants t	to buy 4 kilograms of	oval beads and 5	kilograms of star-shaped beads.	
9	- Cost of oval beads: $4 \text{ kg} \times \frac{2}{\text{kg}} =$	\$8 - Cost of	star-shaped beads: 5	$kg \times \$2/kg = \$10$	)	
)	10tar cost: 58 + 510 = 518 18					
1	Response w/ spurious caption: To	calculate the	e total cost:			
2	1. **Oval beads**: 4 kg at \$3 per kg	g = 4 * 3 =	12 2. **Star-shaped	beads**: 5 kg at	3  per kg = 5 * 3 = 15	
3	$10tar \cos t = $12 + $13 = $27$ 27					
4		Ho	ouses per b	olock		
20						
7		Stem	Leaf			
11			Loon			
98		0	5.7			
97 98 99		0	57			
, 8 9 0 1		0 1	5 7 0 4 5			
		0 1 2	57 045 001233	46789		
		0 1 2 3	57 045 001233 012468	46789		
	Spurious context: Image caption co	0 1 2 3	57 045 001233 012468	46789		
	<b>Spurious context:</b> Image caption cc The diagram is a stem-and-leaf plot	0 1 2 3 mtext: t titled "Hou	5 7 0 4 5 0 0 1 2 3 3 0 1 2 4 6 8 ises per block." It is	<b>4 6 7 8 9</b> used to display of	quantitative data in a compact form,	
	<b>Spurious context:</b> Image caption co The diagram is a stem-and-leaf plot showing the distribution of values. - Title: Houses per block	0 1 2 3 ontext: t titled "Hou	5 7 0 4 5 0 0 1 2 3 3 0 1 2 4 6 8 ises per block." It is	<b>4 6 7 8 9</b> used to display o	quantitative data in a compact form,	
	<b>Spurious context:</b> Image caption co The diagram is a stem-and-leaf plot showing the distribution of values. - Title: Houses per block - Structure: The plot is divided into t	0 1 2 3 ontext: t titled "Hou	5 7 0 4 5 0 0 1 2 3 3 0 1 2 4 6 8 uses per block." It is	<b>4 6 7 8 9</b> used to display o	quantitative data in a compact form,	
	<b>Spurious context:</b> Image caption cc The diagram is a stem-and-leaf plot showing the distribution of values. - Title: Houses per block - Structure: The plot is divided into t - Stem Column: - The stem represen	0 1 2 3 ontext: t titled "Hou two columns ts the hundre	5 7 0 4 5 0 0 1 2 3 3 0 1 2 4 6 8 ises per block." It is : "Stem" and "Leaf." eds digit of the data v	<b>46789</b> used to display o	quantitative data in a compact form, the stem column are: $0, 1, 2, 3$ .	
	<b>Spurious context:</b> Image caption cc The diagram is a stem-and-leaf plot showing the distribution of values. - Title: Houses per block - Structure: The plot is divided into t - Stem Column: - The stem represent - Leaf Column: - The leaf represents are listed in descending order	0 1 2 3 ontext: t titled "Hou two columns ts the hundre s the tens dig	5 7 0 4 5 0 0 1 2 3 3 0 1 2 4 6 8 uses per block." It is : "Stem" and "Leaf." eds digit of the data v git of the data values.	<b>46789</b> used to display of values Values in For each stem	quantitative data in a compact form, the stem column are: 0, 1, 2, 3. value, the corresponding leaf values	
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7 8 9 0 1 2 3 4 5 6 7 8 9 0 1 2 3 4 5 6 7 8	Spurious context: Image caption cc The diagram is a stem-and-leaf plot showing the distribution of values. - Title: Houses per block - Structure: The plot is divided into 4 - Stem Column: - The stem represent are listed in descending order. - Data: - Stem 0: Leaves are 7, 5. Tf numbers 150, 140, and 100 Stem 260, 240, 230, 230, 220, 210, 200, ar 320, 310, and 300. This stem-and-leaf plot provides a cl for easy identification of patterns, su Question: A real estate agent drove blocks have exactly 36 houses? (Uni Response w/o spurious cantion:	0 1 2 3 ontext: t titled "Hou two columns ts the hundre s the tens dig his represent 2: Leaves ar nd 200 Ste ear visual rep ch as cluster around the r t: blocks) To find the n	5 7 0 4 5 0 0 1 2 3 3 0 1 2 4 6 8 uses per block." It is : "Stem" and "Leaf." eds digit of the data v git of the data values. : the numbers 70 and re 9, 8, 7, 6, 4, 3, 3, 2 : m 3: Leaves are 8, 6, presentation of the di ing and spread of the neighborhood and con umber of blocks with	<b>46789</b> used to display of values Values in - For each stem 50 Stem 1: L 2, 1, 0, 0. This re 4, 2, 1, 0. This re stribution of the re data. unted the number	puantitative data in a compact form, the stem column are: 0, 1, 2, 3. value, the corresponding leaf values eaves are 5, 4, 0. This represents the presents the numbers 290, 280, 270, presents the numbers 380, 360, 340, number of houses per block, allowing of houses on each block. How many es, look at the stem "3" and the leaf	
	Spurious context: Image caption cc The diagram is a stem-and-leaf plot showing the distribution of values. - Title: Houses per block - Structure: The plot is divided into t - Stem Column: - The stem represent - Leaf Column: - The leaf represents are listed in descending order. - Data: - Stem 0: Leaves are 7, 5. Tf numbers 150, 140, and 100 Stem 260, 240, 230, 230, 220, 210, 200, ar 320, 310, and 300. This stem-and-leaf plot provides a cl for easy identification of patterns, su Question: A real estate agent drove blocks have exactly 36 houses? (Uni Response w/o spurious caption: T "6" in the stem-and-leaf plot.	0 1 2 3 ontext: t titled "Hou two columns ts the hundre s the tens dig his represent 2: Leaves ar nd 200 Ste ear visual rej ch as cluster around the r t: blocks) To find the n	5 7 0 4 5 0 0 1 2 3 3 0 1 2 4 6 8 uses per block." It is "Stem" and "Leaf." eds digit of the data v git of the data values. s the numbers 70 and re 9, 8, 7, 6, 4, 3, 3, 2 m 3: Leaves are 8, 6, presentation of the di ing and spread of the neighborhood and con umber of blocks with	<b>46789</b> used to display of values Values in - For each stem 150 Stem 1: L 2, 1, 0, 0. This re 4, 2, 1, 0. This re stribution of the re data. unted the number n exactly 36 hous	puantitative data in a compact form, the stem column are: 0, 1, 2, 3. value, the corresponding leaf values eaves are 5, 4, 0. This represents the presents the numbers 290, 280, 270, presents the numbers 380, 360, 340, number of houses per block, allowing of houses on each block. How many es, look at the stem "3" and the leaf	
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97 98 99 00 01 02 03 04 05 06 07 08 09 10 11 12 13 14 15 16 17 18 19 20 21 22 23	<ul> <li>Spurious context: Image caption cc The diagram is a stem-and-leaf plot showing the distribution of values.</li> <li>Title: Houses per block</li> <li>Structure: The plot is divided into t</li> <li>Stem Column: - The stem represent are listed in descending order.</li> <li>Data: - Stem 0: Leaves are 7, 5. Th numbers 150, 140, and 100 Stem 260, 240, 230, 230, 220, 210, 200, an 320, 310, and 300.</li> <li>This stem-and-leaf plot provides a cl for easy identification of patterns, su Question: A real estate agent drove blocks have exactly 36 houses? (Uni Response w/o spurious caption: T "6" in the stem-and-leaf plot.</li> <li>There is 1 block with exactly 36 hou Final value: 1</li> <li>Response w/ spurious caption: T values in the plot are 30 and 40, but Therefore, the number of blocks with</li> </ul>	0 1 2 3 ontext: t titled "Hou two columns ts the hundre s the tens dig his represent 2: Leaves ar nd 200 Ste ear visual rej ch as cluster around the n t: blocks) To find the n ses. The stem-and not 36. h exactly 36	5 7 0 4 5 0 0 1 2 3 3 0 1 2 4 6 8 uses per block." It is "Stem" and "Leaf." eds digit of the data v git of the data values. "Sthen numbers 70 and re 9, 8, 7, 6, 4, 3, 3, 2 "m 3: Leaves are 8, 6, presentation of the di ing and spread of the neighborhood and con umber of blocks with I-leaf plot does not s houses is 0.	<b>46789</b> used to display of ralues Values in - For each stem 150 Stem 1: L 2, 1, 0, 0. This re 4, 2, 1, 0. This re stribution of the re data. unted the number n exactly 36 hous how any blocks of	puantitative data in a compact form, the stem column are: 0, 1, 2, 3. value, the corresponding leaf values eaves are 5, 4, 0. This represents the presents the numbers 290, 280, 270, epresents the numbers 380, 360, 340, number of houses per block, allowing of houses on each block. How many es, look at the stem "3" and the leaf with exactly 36 houses. The closest	

Figure 39: Examples of LMM laziness in MathVista. We mark the *spurious text* in the caption and error in response with red color





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A	B	C	F	
0 0 0 1 1 1	0 0 1 1 0 0 1	0 1 0 1 0 1 0	1 1 1 1 1 1 1	Question: In the circuit shown in figure, the corresponding logical expression is ( ). A. $F = A + B + C$ B. $F = \underline{A \cdot B \cdot C}$ C. $F = \underline{A + B + C}$ D. $F = \overline{A \cdot B \cdot C}$ Answer: D
	11	11	0	

**GPT4-o:** The truth table shows that the output F is 1 for all combinations of A, B, C except when all are 1. This corresponds to the logical expression for a NOR gate, which is the negation of the AND operation. The correct logical expression is:

$$F = \overline{A \cdot B \cdot C}$$

So, the correct option is: D.  $F = \overline{A \cdot B \cdot C}$ 

**Gemini-Pro 1.5:** The truth table shows that F is 0 only when A, B, and C are all 1. This corresponds to a NAND gate. Therefore, the correct logical expression is:

**D.  $F = \overline{A \cdot B \cdot C}$ ** Qwen-VL-Max: The logical expression for the circuit shown in the image is F = A + B + C, which represents the sum of three inputs A, B, and C. Therefore, the correct choice is:

A. F = A + B + CInternVL2-26B: The given circuit is a combination of AND gates. The output F is 1 only when all the inputs A, B, and C are 1. Therefore, the logical expression for F is:

$$F = A \cdot B \cdot C$$

So, the correct option is B. MiniCPM-V-2-6: Answer: D

**LLaVA-v1.6-7b:** The correct option letter is C. The logical expression for the circuit shown in the figure is the complement of the sum of A, B, and C.



**Question:** The logical circuit shown in figure, when A = "0", after the arrival of C pulse, the D flip-flop () A. Has counter function B. Set to "0"

C. Set to "1" D. Uncertain Answer is B Answer: B

**GPT4-o:** When A = "0", the output of the AND gate will be "0" regardless of the other input. Therefore, the D input of the flip-flop will be "0". After the arrival of the C pulse (clock pulse), the D flip-flop will be set to "0".

Answer: B

**Gemini-Pro 1.5:** When A = "0", the output of the AND gate will be "0" regardless of the other input. Therefore, the D input of the flip-flop will be "0". After the arrival of the C pulse (clock pulse), the D flip-flop will be set to "0".

829 Answer: B

Qwen-VL-Max: When A = "0", the AND gate output will be "0" regardless of the value of B. When the C pulse arrives, it will pass through the OR gate and trigger the D flip-flop. Since the input to the D flip-flop is "0" due to the AND gate output, the D flip-flop will set to "0". Therefore, the correct answer is:
B. Set to "0"

**InternVL2-26B:** B. Set to "0"

2834 MiniCPM-V-2-6: Answer: C

**LLaVA-v1.6-7b:** The correct answer is B. The D flip-flop is set to "0" when A = "0" and after the arrival of C pulse.

Figure 41: Examples of responses among 6 baselines in EEE-Bench. The error part os each response is marked as red.

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**Question:** In the circuit shown in figure, it is known that  $u_{i1} = 2V$ ,  $u_{i2} = -2V$ . The output voltage  $u_o$  is ( )V. Answer: -8.

**GPT4-o:** To solve this problem, we need to analyze the circuit, which consists of two operational amplifiers (op-amps) in an inverting configuration.

First Op-Amp: - The first op-amp is in an inverting configuration. - The input voltage  $u_{i1} = 2V$ . -The resistors  $R_1$  and R form the feedback network.

The voltage at the output of the first op-amp,  $u_{o1}$ , is given by the inverting amplifier formula:

$$u_{o1} = -\left(\frac{R}{R_1}\right)u_{i1}$$

Assuming  $R = R_1$ , we have:  $u_{o1} = -2V$ 

Second Op-Amp: - The second op-amp is also in an inverting configuration. - The input voltage  $u_{i2} = -2V$ . - The resistors  $R_2$  and R form the feedback network.

The voltage at the output of the second op-amp,  $u_o$ , is given by:

$$u_o = -\left(\frac{R}{R_2}\right)\left(u_{o1} + u_{i2}\right)$$

Assuming  $R = R_2$ , we have:

$$u_o = -(u_{o1} + u_{i2}) = -(-2V - 2V) = 4V$$

Therefore, the output voltage  $u_o$  is 4.0 volts.

**Gemini-Pro 1.5:** The circuit shown is a two-stage inverting amplifier. The gain of each stage is determined by the ratio of the feedback resistor to the input resistor. Since the open-loop gain of the op-amps is infinite, the voltage at the inverting input of each op-amp is equal to the voltage at the non-inverting input, which is 0V. For the first stage, the output voltage  $u_{o1}$  can be calculated as:

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$$u_{o1} = -\frac{R}{R}u_{i1} = -u_{i1} = -2V$$

**2869** For the second stage, the output voltage  $u_o$  can be calculated as:

**2870** 
$$u_{0} = -\frac{R}{R}u_{01} = -u_{01} = 2V$$

2871 Therefore, the output voltage  $u_o$  is **2.0**.

**Qwen-VL-Max:** The circuit shown in the image is a simple voltage divider circuit. To find the output voltage  $u_o$ , we need to calculate the voltage across the resistor  $R_2$  using Ohm's law.

Ohm's law states that V = IR, where V is the voltage, I is the current, and R is the resistance.

In this case, the voltage across  $R_2$  can be calculated as follows:  $V_{R2} = I * R_2$  First, let's find the total resistance of the circuit  $(R_T)$ :  $R_T = R + R_1 + R_2$  Then, we can find the current through the circuit (I) by dividing the input voltage  $(u_{i1})$  by the total resistance:  $I = \frac{u_{i1}}{R_T}$  Finally, we can calculate the voltage across  $R_2$   $(V_{R2})$ :  $V_{R2} = I * R_2$ 

2878 Since  $u_i 1 = 2V$  and  $u_i 2 = -2V$ , the net input voltage is zero. Therefore, the output voltage  $u_o$  will also be zero.

2880 So, the output voltage  $u_o$  is 0.0 V.

**InternVL2-26B:** To determine the output voltage  $u_o$  in the given circuit, we need to analyze the circuit and apply the appropriate rules for resistors and operational amplifiers.

2883 1. **Identify the Operational Amplifiers (Op-Amps):** - The circuit has two operational amplifiers, each with 2884 an input resistance of R and a feedback resistance of  $R_1$  and  $R_2$  respectively.

2. **Determine the Input Voltage for Each Op-Amp:** - For the left Op-Amp: -  $u_{i1} = 2V - u_{i2} = -2V$  - For the right Op-Amp: -  $u_{i1} = u_o - u_{i2} = u_o$ 

3. **Apply the Op-Amp Voltage Rule:** - The voltage difference between the inverting and non-inverting inputs of each Op-Amp must be zero for proper operation. - For the left Op-Amp:

$$u_{i1} - u_{i2} = 2V - (-2V) = 4V$$

This indicates that the left Op-Amp is not functioning correctly, as the voltage difference is not zero.

4. **Analyze the Circuit Configuration:** - The circuit configuration suggests that the resistors R and  $R_1$  are connected in series with the left Op-Amp, and R and  $R_2$  are connected in series with the right Op-Amp. - The output voltage  $u_o$  is connected to both Op-Amps, indicating that the circuit is likely designed to sum the input voltages.

2895 5. **Summing the Input Voltages:** - Since the circuit is designed to sum the input voltages, we can write the 2896 equation for  $u_o$ :  $u_o = u_{i1} + u_{i2}$  - Substituting the given values:

$$u_o = 2V + (-2V) = 0V$$

Therefore, the output voltage  $u_o$  is 0V.

Figure 42: Examples of responses among 4 baselines in EEE-Bench, where all baselines fail to reason correctly for this problem.