CharXiv: Charting Gaps in Realistic Chart Understanding in Multimodal LLMs

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Abstract

Chart understanding plays a pivotal role when applying Multimodal Large Language Models (MLLMs) to real-world tasks such as analyzing scientific papers or financial reports. However, existing datasets often focus on oversimplified and homogeneous charts with template-based questions, leading to an overly optimistic measure of progress. We demonstrate that although open-source models can appear to outperform strong proprietary models on these benchmarks, a simple stress test with slightly different charts or questions can deteriorate performance by up to 34.5%. In this work, we propose CharXiv, a comprehensive evaluation suite involving 2,323 natural, challenging, and diverse charts from arXiv papers. CharXiv includes two types of questions: 1) descriptive questions about examining basic chart elements and 2) reasoning questions that require synthesizing information across complex visual elements in the chart. To ensure quality, all charts and questions are handpicked, curated, and verified by human experts. Our results reveal a substantial, previously underestimated gap between the reasoning skills of the strongest proprietary model (i.e., GPT-40), which achieves 47.1% accuracy, and the strongest open-source model (i.e., InternVL Chat V1.5), which achieves 29.2%. All models lag far behind human performance of 80.5%, underscoring weaknesses in the chart understanding capabilities of existing MLLMs. We hope that CharXiv facilitates future research on MLLM chart understanding by providing a more realistic and faithful measure of progress.

1 Introduction

Multimodal Large Language Models (MLLMs) [4, 56, 14, 82, 54, 16, 17, 12, 40, 41, 7, 2, 5, 73, 78, 49] are highly versatile and effective for a wide range of real-world applications [64, 69, 20, 57, 92, 61, 68, 60, 93]. Within these applications, chart understanding is a highly desired capability as charts are ubiquitous in scientific papers, financial reports, and news articles. It also poses unique challenges where models need to perform complex reasoning over numerical data, textual labels, and complex visual elements to answer difficult questions (see Fig. 1), thus making chart understanding a suitable measure of progress for MLLMs. Many benchmarks in the popular MathVista evaluation suite [60] are designed to test chart understanding. However, these benchmarks lack diversity in both the types and complexity of the charts and the often template-based questions (§2.1). For example, FigureQA [36] and DVQA [35] rely on procedurally generated question templates. While ChartQA [64] includes a mixture of handwritten and machine-generated questions, the charts lack visual diversity due to the homogeneous appearance of the charts from a limited number of sources. Regardless, many proprietary models [2, 78, 5, 73] and open-source models [12, 17, 16, 41, 31, 49, 55, 21] are evaluated

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Figure 1: Example chart (left), descriptive questions (top-right) and reasoning questions (bottomright) in CharXiv where open-source models even fail in basic descriptive questions. Moreover, all models struggle with correctly answering the reasoning question.

on these datasets.¹ These narrow evaluations create the appearance that the open-source models outperform proprietary ones², despite evidence to the contrary: we designed simple stress tests ($\S2.2$) in which we find that open-source models lag far behind proprietary ones in their robustness to small visual or textual changes. For example, the accuracy of SPHINX V2 dropped from 63.2% to 28.6% with a 34.5% gap when questions are slightly modified with respect to the same set of charts.

We introduce CharXiv, a comprehensive evaluation suite for complex understanding of natural, challenging, and diverse charts (§3) to address the above issue. CharXiv consists of 2,323 real-world charts handpicked from scientific papers spanning 8 major subjects published on arXiv (§3.1). We explicitly disentangle visual understanding and reasoning by designing two types of questions (§3.2): (1) *descriptive* questions, requiring understanding basic chart information such as the title, labels, and ticks; (2) *reasoning* questions, requiring comparisons, approximations, and fine-grained analysis. CharXiv is an especially high-quality dataset where all questions are *manually* curated by human experts, and all ground-truth answers are validated by hand. To answer both types of questions, the model only needs to understand the visual contents of the chart without advanced domain-specific knowledge and contextual information. Evaluating an MLLM on CharXiv is straightforward, because we impose a short answer format that is amenable to LLM-based automatic grading.

We extensively evaluate 13 open-source models and 11 proprietary models (§4.1) and identify a large disparity between the strongest open-source and proprietary models (§4.2): InternVL Chat V1.5 correctly answers only 29.2% of the reasoning questions and 58.5% of the descriptive ones, whereas GPT-40 correctly answers 47.1% of the reasoning questions and 84.5% of the descriptive ones (Tab. 3). As shown in Fig. 2, the performance gap in the reasoning questions of 17.9% is significantly larger than the gap identified in prior works [35, 36, 64]. Further, both types of models lag far behind the human performance of 80.5% on the reasoning questions and 92.1% on the descriptive ones. Fine-grained analysis of model performance (§4.3) shows several insights owing to the design of CharXiv. In particular, we characterize: (1) differences in reasoning and descriptive capabilities, exploring when one skill reinforces the other; (2) what types of tasks and charts are difficult for existing MLLMs; (3) how different MLLMs respond to unanswerable questions. Overall, we hope that CharXiv enables a thorough, multi-faceted evaluation of chart understanding in MLLMs.

¹We note that there are several more sophisticated benchmarks [86, 85, 53] that have recently been released. We discuss key differences between CharXiv and these benchmarks in §2.1.

²See the FQA (*i.e.*, Figure QA) column of the MathVista leaderboard. Throughout the paper, "open-source" refers to models with publicly available weights.



Figure 2: Model performance comparison on reasoning questions from CharXiv v.s. questions from existing benchmarks. As indicated by the red and blue bars resepctively, many open-source models surpass proprietary model performance on the 174 sample questions from existing benchmarks (subsets of DVQA, FigureQA and ChartQA from the *testmini* split of MathVista) yet fail consistently on the 1000 reasoning questions from the validation split of CharXiv.

2 Existing Benchmarks Overestimate Chart Understanding Capabilities

2.1 Related Works

Existing benchmarks such as FigureQA [36], DVQA [35], PlotQA [71] do not fully capture the complexity and diversity of real-world charts due to their synthetic nature, while charts in ChartQA [64] lack visual diversity. More recent benchmarks such as MMC [53], ChartBench [86] and ChartX³ [85] also contain issues with the source or diversity of the charts (*e.g.*, ChartX, MMC) and the types of questions (*e.g.*, MMC, ChartBench). We provide a summary of existing benchmarks' design choices in Tab. 1 and a detailed review below. We provide a more detailed related works on Multimodal Large Language Models and More MLLM benchmarks in App. B.

Chart source. FigureQA, DVQA and PlotQA use plotting software to synthesize charts restricted to very few predefined chart types with stylistically similar elements (see Figs. 8(a), 8(b) and 8(c)). ChartQA sources charts from only 4 websites, each of which lacks visual diversity (see Fig. 8(d)). One such website also served as the primary source of charts for reasoning questions in MMC. On the other hand, ChartX provides fixed instructions to GPT-4 to write code to procedurally generate predefined types of charts and settings in bulk. All of these approaches yield artificial charts belonging to a narrow distribution.

Question types. Existing benchmarks lack variation in their questions: FigureQA, DVQA and PlotQA use a fixed template to generate QA pairs, while Table 1: Design choice of chart understanding benchmarks. We use the following shorthand: Vis. Div.=visual diversity, Temp.=template, Knwl.=knowledge, and Vocab.=vocabulary. Cells marked with "" indicate *mixed attributes* (e.g., real and synthetic data; real and synthetic chart).

				Түре	ANSWER		
Name	Real Data	Real Chart	Vis. Div.	Temp. Based	Free Form	Knwl. Free	Open Vocab.
QA-Based							
FigureQA [36]	X	×	X	\checkmark	×	\checkmark	×
DVQA [35]	X	X	X	\checkmark	×	\checkmark	\checkmark
PlotQA [71]	\checkmark	×	X	\checkmark	×	\checkmark	\checkmark
ChartQA [64]	1	\checkmark	X	X	\checkmark	\checkmark	\checkmark
ChartBench [86]	×	×	\checkmark	\checkmark	×	\checkmark	×
Multi-Task							
MMC [53]	1	1	X	X	1	X	\checkmark
ChartX [85]	×	×	\checkmark	×	\checkmark	\checkmark	\checkmark
CharXiv	\checkmark	1	1	1	\checkmark	1	1

ChartBench adopts an automatic QA generation pipeline according to 4 predefined tasks. However, similar to MMMU [93], more complex reasoning questions from MMC cannot be solved from the charts alone and require external domain-specific knowledge (e.g., mapping acronyms in the legend to particular algorithms).

Answer & validation. FigureQA and ChartBench both evaluate model performance based only on *yes/no* questions. Evaluating models on binary answers does not faithfully reflect their performance in the natural use case of general free-form question answering [48].

2.2 Open-Source MLLMs Are Sensitive to Perturbations

Many open-source models have adapted the training sets of existing benchmarks [36, 35, 64] for visual instruction tuning [56] and show promising performance in their respective evaluation sets. However, due to the aforementioned issues with the diversity of these benchmarks, the evaluation

³Due to limited public availability of the MMC and ChartBench data, our assessment is based on the papers.

data is too similar to the training data. As a result, evaluation scores often do not accurately reflect the general chart understanding capabilities of MLLMs. In particular, we demonstrate below that *simple* modifications in the evaluation components lead to *drastic* changes in model performance.

Models. We selected open-source models that are known to be trained on the training set of DVQA and ChartQA: Mini-Gemini (MGM) [49], InternVL-XComposer2 (IXC2) [16], InternVL-XComposer2 4KHD (IXC2 4KHD) [17], InternVL-Chat V1.5 [12], SPHINX V2 [21], LLaVA 1.6 [55], and IDEFICS 2 [41]. We compare their performance with proprietary models [2, 5, 73].



Figure 3: Open-source models generalize poorly to modified examples (measured by accuracy). Left: original set against modified-*question* set. Right: original set against modified-*chart* set.

Evaluation set. We extracted subsets of DVQA, FigureQA, and ChartQA from MathVista. This yields 174 samples, and we refer to it as the *original set*. To test the robustness of the models mentioned above, we created two modified versions of the original set: the modified-question set (see App. S) and the modified-chart set (see App. T). In the modified-question set, we retain the original chart, but write novel questions that deviate from the predefined templates [36, 35]. In the modified-chart set, we alter the charts to those from arXiv with similar visual complexity that can be asked with the same types of questions. We manually annotate all questions and answers in both the modified-question and the modified-chart set. As in the original set, we maintain an equal number of yes and no answers in the original set to prevent models from achieving artificially high scores by simply outputting one response more often than the other, and adopt the same evaluation protocol as in MathVista.

Results. As plotted in Fig. 3, all proprietary models remain close to the diagonal line, indicating good generalization in both modified-question and modified-chart scenarios. In contrast, most open-source models exhibit significant performance degradation in both settings, indicating poor generalization. We observe the most pronounced performance drop in SPHINX V2 in the modified-question set, where performance dropped by 34.5%, from 63.2% in the original set to 28.7% in the modified-question set. Our findings demonstrate that design strategies in existing benchmarks lead to an *overestimation* of chart understanding capabilities for open-source models. We hypothesize that the training and evaluation datasets are too similar, so models appear to generalize well despite not being robust to simple modifications. In the next section, we introduce CharXiv, which features a more natural, challenging, and diverse evaluation of real-world charts.

3 CharXiv: A Real-World and Challenging Chart Understanding Benchmark

CharXiv is a comprehensive and challenging chart understanding benchmark sourced solely from real-world charts. We select diverse, naturally occurring, and complex figures from arXiv preprints, and manually construct descriptive and reasoning questions that require intensive visual and numerical analysis. CharXiv consists of 2,323 charts paired with more than 10K questions—we randomly sample 1,000 charts as the validation set and use the rest as the test set.⁴ In the following sections, we describe how we select charts (§3.1), construct questions (§3.2), and validate model responses (§3.3).

⁴Similar to MathVista [60] and MMMU [93], we release all QA pairs for the validation set and keep the answers to the test set private to prevent data leakage.

Chart Metadata <u>Categories</u>	Reasoning Questions	Descriptive Questions
Computer Science (292; 12.6%) Economics (287; 12.3%) Elec. Eng. & Sys. Sci. (291; 12.5%) Mathematics (286; 12.3%) Physics (294; 12.7%)	Text in Chart (1044; 45%) Number in Chart (512; 22.0%) Text in General (229; 9.9%) Number in General (538; 23.2%)	Title (591; 6.4%) Continuous Legend: x-axis Label (519; 5.6%) • max value (724; 7.8%) y-axis Label (494; 5.3%) • range [max - min] (695; 7.5%) Leftmost Tick (586; 6.3%)
Physics (294; 12.7%) Quant. Biology (293; 12.6%) Quant. Finance (289; 12.4%) Statistics (291: 12.5%)	QA Source GPT-Generated (448; 19.3%) GPT-Inspired (497; 21.4%)	Rightmost Tick (581; 6.3%) • x-axis ticks (490; 5.3%) Lowest Tick (570; 6.1%) • y-axis ticks (499; 5.4%) Highest Tick (537; 5.8%) Discrete Labels (492; 5.3%)
Year Number of Subplo	Human-Written (1378; 59.3%)	Pattern Recognition Counting
2020 (581; 25.0%) 2021 (585; 25.2%) 2022 (584: 25.2%) 2-4 (876; 37.7%)	Answerability	Trend of Data (85; 0.9%) # Lines (471; 5.1%) Subplot Layout (566; 6.1%) # Subplots (144; 1.6%)
2022 (304, 23.1%) 5+ (551; 23.7%) 2023 (573; 24.7%)	Unanswerable (2323; 25%)	Compositionality # tick labels across all axes (566; 6.1%

Figure 4: Metadata breakdown of charts, descriptive questions, and reasoning questions in CharXiv.

3.1 Chart Curation

Figure source. We downloaded all arXiv preprints on eight academic subjects from January 2020 to September 2023 (Fig. 4) and extracted figures from the source files. All figures were re-rendered into high-resolution JPEG format, with the longer side of each figure resized to 1024px.

Chart selection. We define a chart as *any figure that visually illustrates data*. Most figures in arXiv source files are diagrams, illustrations, and natural images, *not* charts. To identify charts and promote visual diversity, we apply a four-step selection pipeline. First, we utilize a pretrained SigLIP visual encoder [94] to identify candidate figures that exhibit a cosine similarity of at least 0.65 with the average image embedding of existing charts from MathVista [35, 36, 64, 60]. We choose this target similarity to balance identifying charts and ensuring good coverage of the visually diverse distribution. Second, we recruit experienced graduate students to manually select charts from the candidate set. Concretely, we randomly sample 750 candidate figures from the pre-filtered set for each subject and year, and present 10 figures at a time to the annotators, asking them to select a single figure that is a chart and looks different from previously selected datapoints (see App. R.1 for details). In the third step, we remove the charts that exhibit large (≥ 0.95) pairwise cosine similarities with the other candidates. Finally, we remove the charts that are not clearly labeled or appear blurry. At the end of this four-step pipeline, we have 2,323 charts in total.

We provide details of the chart categories, years, and number of subplots in Fig. 4, size information in Tab. 2, and a collage of sampled charts in Fig. 8(e). Notably, the charts in CharXiv exhibit far greater compositional and stylistic complexity compared to those in existing datasets. A single chart often combines elements or subplots featuring multiple chart types (e.g., lines and bars in one plot). To aggregate statistics on chart types, we first query GPT-40 to generate potential chart types for each chart. Human annotators then review and refine this list, assigning a primary chart type based on the chart's most salient features. We provide chart type statistics in Fig. 5.

3.2 Question Construction

We construct two types of questions: *descriptive* and *reasoning*. Descriptive questions assess models' capability in extracting and aggregating basic information from charts, and reasoning questions evaluate a model's ability to perform complex visual reasoning.

Descriptive questions. We designed a total of 19 templates for descriptive questions that require (1) identifying basic information, such as the title, axis labels, legend labels, labeled ticks, or (2) aggregating chart information to count ticks, recognize data patterns, and enumerate labels. These questions are broadly categorized into five groups: information extraction, enumeration, pattern recognition, counting, and compositionality (see App. O.1 for details). Although descriptive questions are intended to be easier than reasoning questions, they can still pose challenges due to the complexity of the charts. For example, answering descriptive questions about charts with multiple subplots requires the model to first identify the relevant subplot⁵ (see Apps. U.1, U.7 and U.10). If basic elements such as the legend, axis, and title are shared across multiple subplots, the model must then also grasp the relationships among the subplots to extract the correct information (see Apps. U.3 and U.23). We pair each chart with four descriptive questions and one of them is intentionally

⁵We use the prefix "for the subplot at row N and column M" when subplots form a grid or a description e.g., "for the bottom left subplot" otherwise. Both N and M start from 1.



Figure 5: Statistics of chart types. CharXiv captures a long tail of chart categories in-the-wild.

designed to be *unanswerable*⁶, where the requested information does not exist or is not applicable to the subplot in the chart. We provide the distribution of specific questions in Fig. 4, aggregated statistics of questions and answers in Tab. 2, and a screenshot of the labeling process in App. R.2.

Reasoning questions. We *manually* craft one reasoning question for each chart to evaluate the models' ability to perform visual and numerical reasoning. To ensure data quality, we recruit graduate students as annotators. Annotators are presented with a chart and 10 sample reasoning QA pairs generated by GPT-4V. Based on the diversity and practicality of the sample questions, annotators choose or modify one of the samples, or they create their own question for each chart. The resulting question must have a definite and unambiguous answer and must strictly adhere to one of the following four types:

- *text-in-chart*: The answer is a piece of text found in the chart (see Apps. V.1, V.2 and V.6).
- *text-in-general*: The answer is an easily verifiable phrase that is not necessarily in the chart (see Apps. V.3, V.4 and V.30).
- *number-in-chart*: The answer is a numerical value written on the chart (see Apps. V.7, V.9 and V.12).
- *number-in-general*: The answer requires an exact numerical value, not necessarily found in the chart, to a specified precision (see Apps. V.5, V.14 and V.15).

One notable feature of our reasoning questions is that they are designed to require *only* visual and numerical reasoning, without the need for advanced domain-specific knowledge or access to captions and referencing paragraphs. This sets CharXiv apart from MathVista [60], MMMU [93], and arXiv-based QA datasets [53, 47, 46], which often require additional expert knowledge. Although our curation process requires significant

Table 2: CharXiv dataset statistics. Unique tokens and question & answer lengths are calculated based on the GPT-40 tokenizer.

Statistics	Value
Charts	
Total Charts	2,323
Total Subjects/Years	8/4
Val:Test	1,000/1,323
Average size (px)	996×702
Maximum size (px)	1024×1024
Descriptive Questions	
# questions	9,292
# unique questions	19
Answer	
 + unique. tokens 	3,723
- maximum length	138
- average length	2.93
Reasoning Questions	
# questions	2,323
# unique questions	2,323
Question	
 # unique tokens 	5,114
- maximum length	144
- average length	22.56
Answer	
 # unique tokens 	2,177
 maximum length 	38
- average length	2.8

human effort to craft question-answer pairs, we believe that it promotes originality, diversity, accuracy, and answerability. The distribution for both QA sources and answer types is shown in Fig. 4 and the aggregated statistics of the questions and answers are shown in Tab. 2. We provide a screenshot of the annotation interface in App. R.3, and the response generation instructions for each type of answer in App. P.1.

3.3 Evaluation Metrics

CharXiv is amenable to automatic grading due to the unambiguous nature of the answers. Considering the fact that many charts contain Greek symbols and math notation that can be typed in different ways (*e.g.*, α and λ alpha\$; T^a_b and T_b^a), we opt out of exact match and instead use GPT-40 [2] to extract the answer, compare with the human reference for consistency, and assign *binary* scores based on the correctness. This procedure can be considered an LLM judge based on human reference.

⁶This is inspired by similar designs in SQuAD 2.0 [75] and WebArena [99].

Similar GPT-assisted evaluations have become commonplace in many established benchmarks [60, 92, 18]. Grading instructions for descriptive and reasoning questions are provided in App. O.2 and App. P.2 respectively. To verify the effectiveness and fairness of the judge, we also performed human annotation in which we graded a total of 400 descriptive and reasoning questions in 4 models. Grades from GPT-40 and humans on models' responses match 98.5% of the time. We provide detailed metrics in Tab. 18 and Tab. 19.

4 Experiments

4.1 Experimental Setup

Models. We evaluate a diverse set of general-purpose multimodal large language models (MLLMs) that can (1) process input resolution greater than or equal to 448 × 448 and (2) achieve a score of at least 36 on the *testmini* set of MathVista [60]. For open-source models, we test: InternVL Chat V1.5 [12], InternLM-XComposer2-4KHD (IXC2 4KHD) [17], InternLM-XComposer2 (IXC2) [16], LLaVA 1.6 Yi 34B [55], LLaVA 1.6 Mistral 7B [55], DeepSeek VL [59], MoAI [42], IDEFICS 2 [41], IDEFICS 2 Chatty [41], SPHINX V2 [21], Mini-Gemini (MGM) HD Yi 34B [49], Mini-Gemini (MGM) HD LLaMA3 8B [49], and MiniCPM-V2 [31] (See more model details in Tab. 16). We also evaluate the following proprietary models: GPT-40 [2], GPT-4V [2], Claude-3 Opus [5], Claude 3 Sonnet [5], Claude 3 Haiku [5], Reka Core [73], Reka Flash [73], Reka Edge [73], Gemini 1.0 Pro [78], Qwen VL Plus [7], and Qwen VL Max [7]. For all models, we provide generation configurations in Tab. 15.

Baselines. We provide a text-only baseline, denoted as Random (GPT-4o), where we prompt GPT-4o to reasonably guess the answer without seeing the charts (see the prompt in App. Q). This accounts for the effect of using common sense or shallow cues in textual queries to correctly guess the answer. We also recruit in-house human participants and report their performance (*i.e.*, Human) on CharXiv. Notably, we ensure that the participants see the exact same questions and instructions as the models and that their responses are evaluated in the same way as the models' responses. This approach allows us to fairly compare the performance gap between humans and models.

4.2 Experimental Results

We provide quantitative results on the validation set for all models in Tab. 3⁷. Results on the test set are available in Tab. 5. To better understand where models fail, we select a set of representative models [2, 5, 73, 12, 49, 41] and present examples of failure cases for 30 descriptive questions in App. U and 30 reasoning questions in App. V. The latest results are in our leaderboard.

All models struggle with reasoning questions. As shown in Tab. 3, the top-performing model, GPT-40, only correctly answers 47.1% of the reasoning questions, exhibiting a 33.4% gap to the human performance of 80.5%. Moreover, the strongest open-source model, InternVL Chat V1.5, only correctly answers 29.2% of the reasoning questions, highlighting a substantial gap between the leading proprietary and open-source models. Notably, none of the other open-source models can correctly answer more than 25% of the reasoning questions, indicating marked weaknesses in handling the diverse and challenging chart reasoning questions in CharXiv despite achieving decent performance in existing benchmarks [35, 36, 64, 60] (*e.g.*, see Fig. 2).

Open-source models still struggle with descriptive questions. The leading proprietary model, GPT-40, exhibits strong capabilities in answering descriptive questions, lagging just 7.65% behind human performance. However, similar to our findings on reasoning questions, the top-performing open source model, InternVL Chat V1.5, exhibits a 25.95% drop in performance compared to GPT-40. Overall, the performance of open-source models on descriptive questions remains very low, with most models failing to correctly answer more than 50% of questions.

4.3 Analysis

Descriptive skills are a prerequisite for reasoning. We find that models with strong reasoning capabilities exhibit strong descriptive capabilities, but the reverse is *not* guaranteed (e.g., see Gemini

⁷Results for Tab. 3 have a cutoff date of June 12, 2024. For additional evaluations conducted after June 12, 2024 and before October 30, 2024, we provide the results in Tab. 4.

Table 3: Evaluation results on the validation set. Bold numbers represent the best in-class performance (open-source or proprietary), and <u>underlined</u> numbers represent the second-place. Models with (*) are those whose performance is constrained by input resolutions (see Tab. 16 for details). Info. Extr.=information extraction, Enum.=enumeration, Patt. Rec.=pattern recognition, Cntg.=counting, Comp.=compositionality. Details for these categories are shown in Fig. 4 and §3.2. *Cutoff date: June 12, 2024. Evaluation results on more models are provided in Tab. 4.*

		Rea	soning Qu	estions			D	Descriptive Questions			
Model	All	Text in Chart	Text in General	Num. in Chart	Num. in General	All	Info. Extr.	Enum.	Patt. Rec.	Cntg.	Comp.
Baselines											
Human	80.50	77.27	77.78	84.91	83.41	92.10	91.40	91.20	95.63	93.38	92.86
Random (GPT-40) [2]	10.80	4.32	39.39	5.60	16.16	19.85	21.65	16.71	23.80	25.70	5.36
Proprietary Multimodal Large Language Models											
GPT-40 [2]	47.10	50.00	61.62	47.84	34.50	84.45	82.44	89.18	90.17	85.50	59.82
GPT-4V [2]	<u>37.10</u>	<u>38.18</u>	<u>57.58</u>	37.93	25.33	<u>79.92</u>	78.29	<u>85.79</u>	88.21	80.92	<u>41.07</u>
Claude 3 Sonnet [5]	32.20	31.59	50.51	31.47	26.20	73.65	75.74	81.92	76.64	72.26	8.48
Claude 3 Haiku [5]	31.80	29.77	45.45	34.48	27.07	65.08	69.87	69.98	64.85	61.83	8.04
Claude 3 Opus [5]	30.20	26.36	50.51	33.62	25.33	71.55	75.62	73.69	73.58	70.48	26.79
Reka Core [73]	28.90	27.50	41.41	28.45	26.64	55.60	58.90	50.52	65.72	71.25	10.71
Reka Flash [73]	26.60	26.59	39.39	30.60	17.03	56.45	61.39	48.59	69.87	72.52	7.14
Qwen VL Max [7]	24.70	26.14	41.41	24.57	14.85	41.48	50.42	28.41	53.71	51.15	4.46
Reka Edge [73]	23.50	20.23	32.32	30.60	18.78	33.65	36.65	28.49	34.72	52.16	4.91
Gemini 1.0 Pro [78]	22.80	20.91	48.48	18.10	20.09	54.37	67.97	39.23	60.48	62.60	8.93
Qwen VL Plus [7]	16.00	15.45	45.45	12.07	8.30	28.93	33.33	17.92	32.10	56.23	2.23
		Open-So	ource Mult	imodal La	rge Langua	age Model	5				
InternVL Chat V1.5 [12]	29.20	30.00	45.45	32.33	17.47	58.50	69.63	52.95	53.06	64.63	5.80
MGM HD Yi 34B [49]	25.00	26.59	43.43	27.16	11.79	52.68	53.86	55.04	65.50	53.94	2.23
IXC2 4KHD [17]	25.00	23.86	43.43	29.31	14.85	54.65	61.09	54.08	51.53	59.80	6.70
LLaVA 1.6 Yi 34B* [55]	22.50	20.45	37.37	23.71	18.78	51.05	46.38	63.44	56.11	51.91	5.80
MGM HD LLaMA3 8B [49]	19.00	19.77	36.36	21.12	7.86	44.42	49.41	39.23	51.09	55.98	1.79
IXC2* [16]	18.70	16.14	38.38	21.98	11.79	38.75	34.10	43.58	46.72	52.93	5.80
MiniCPM-V2 [31]	18.50	17.95	33.33	19.40	12.23	35.77	39.74	36.56	26.42	44.53	5.36
IDEFICS 2 [41]	18.20	15.45	35.35	17.24	17.03	32.77	36.12	27.28	40.83	43.26	3.12
IDEFICS 2 Chatty [41]	17.80	15.45	34.34	19.83	13.10	41.55	34.88	54.56	45.63	44.27	6.70
MoAI* [42]	17.50	9.32	36.36	21.12	21.40	28.70	31.20	21.23	39.96	40.46	7.59
DeepSeek VL [59]	17.10	16.36	32.32	19.83	9.17	45.80	49.11	45.20	42.79	60.31	4.91
SPHINX V2* [21]	16.10	13.86	28.28	17.67	13.54	30.25	35.59	24.37	41.05	29.52	1.79
LLaVA 1.6 Mistral 7B* [55]	13.90	11.36	32.32	16.81	7.86	35.40	34.70	33.98	48.91	42.49	8.48

1.0 Pro, IDEFICS 2 Chatty and DeepSeek VL in Tab. 3). Manual inspection of models' answers to reasoning questions reveals that some models [73, 49, 7, 42] leverage zero-shot Chain-of-Thought (CoT) reasoning [84, 97] to answer the reasoning questions. However, such CoT may not always be helpful, especially when models cannot accurately describe the chart, as we show in Apps. U.13, U.28, V.1 and V.17. Quantitatively, we show in App. I that longer responses (*e.g.*, those potentially containing more CoT traces) can *negatively* impact models' performance on reasoning questions. This issue is especially clear in models with low accuracy on descriptive questions, such as MoAI and Qwen VL Plus, which answer 28.70% and 28.93% of descriptive questions correctly. In contrast, models with higher accuracy on descriptive questions, such as Mini-Gemini HD Yi 34B and Reka Flash, which achieve 52.68% and 56.45%, respectively, show improved performance on reasoning questions when generating lengthy responses. Nevertheless, the vast majority of models exhibit performance uncorrelated with response length. Thus, we hypothesize that a model must have a strong basic understanding in order to generate helpful multimodal CoT for reasoning.

Models struggle with compositional tasks that are easy for humans. We find that the descriptive task that most strongly differentiates the capabilities of the leading open-source, the top-performing proprietary model, and humans is to count the number of labeled ticks on the x- and y-axes (see App. U.28), on which they achieve 92.86%, 59.82% and 5.80% accuracy respectively. Although counting is easy for humans, this particular task causes 20 out of 24 models to achieve an accuracy below 10% (our random baseline achieves 5.35%). While we do not specifically measure how close each model's responses are to the ground truth, a near-random performance pinpoints the weakness of MLLMs in solving compositional and novel chart understanding tasks.

Weak models cannot identify unanswerable questions. CharXiv is the first work to introduce unanswerable questions in chart understanding. As discussed in §3.2, 25% of descriptive questions are designed to be unanswerable, where the requested information does not exist or is not applicable to the target subplot in the chart (see Apps. U.2, U.4, U.6, U.12, U.14, U.16, U.18, U.20, U.22, U.24 and U.26). We measure how often models can correctly identify and suitably respond to unanswerable



Figure 6: Analysis on unanswerable questions (a) and charts with subplots (b).

questions in Fig. 6(a). Interestingly, the models that achieve an accuracy below 80% on unanswerable questions each exhibit idiosyncratic patterns of failure. For example, IDEFICS 2 Chatty incorrectly responds to nearly 90% unanswerable questions about the title, x- and y-axis labels, yet correctly identifies more than 90% of unanswerable questions about intersections of lines and the presence of the legend. On the other hand, IXC 2 correctly respond to 80% questions about names of title, x- and y-axis labels that are unanswerable, yet fails to identify unanswerable cases for the difference in tick values when ticks are categorical or the difference is not constant.

In addition, we evaluate models' performance on descriptive questions *without* unanswerable questions in Tab. 12, and find that the overall performance for the majority of the proprietary models appears to benefit from the exclusion of unanswerable questions, while most open-source models exhibit degraded overall performance when unanswerable questions are excluded.

Descriptive capabilities degrade with more subplots. CharXiv is the first work to aggregate detailed statistics on the number of subplots in each chart, so we are able to conduct a fine-grained analysis of how the performance of proprietary models and open-source models changes with the number of subplots in the chart. As shown in Figure 6(b), a representative set of open-source and proprietary models struggle to answer descriptive questions about charts with more subplots. With 6+ subplots, the deterioration is 30%–50% for open-source models and only 10%–30% for proprietary models. This indicates that all MLLMs are weaker in handling descriptive queries for charts with more subplots, and such performance deterioration is exacerbated in open-source models. We hypothesize that this is because open-source models are instruction-tuned on chart datasets that do not contain subplots, such as DVQA and ChartQA. On the other hand, there appears to be no clear correlation between reasoning capabilities and the number of subplots.

Model performance varies among different subjects. Although the questions in CharXiv are designed to be answerable without domain-specific knowledge, we measure the models' performance on individual subjects (see Fig. 4). All models show consistently weaker descriptive capabilities on physics-related charts and stronger performance on charts containing electrical engineering and systems science, quantitative finance, and economic data (see Tab. 6). On the other hand, models exhibit idiosyncratic reasoning capabilities over different subjects, demonstrating no clear pattern (see Tab. 7). Interestingly, the strongest open-source model, InternVL Chat V1.5, matches GPT-4V in correctly answering 39.26% of the reasoning questions from charts in the math domain, but it significantly lags behind in other domains, exhibiting gaps greater than 20% in the physics and electrical engineering and systems science domains. These patterns suggest that (1) charts from certain domains are inherently difficult for models to describe and (2) there exist unique skills that are required to perform complex reasoning over charts from different domains.

Model performance varies across chart types. Our analysis of model performance across different chart types is presented in Tab. 13 for descriptive questions and Tab. 14 for reasoning questions. For descriptive questions, both proprietary and open-source models generally underperform on less

common chart types, such as contour plots and heatmaps (see Fig. 5). GPT-40, the best-performing model, demonstrates a noteworthy exception to this trend. While its advantage over GPT-4V is modest for common chart types (line, scatter, and bar charts), it substantially outperforms other models on less common chart types, such as heatmaps and contour plots, suggesting better generalization across diverse chart types. However, all models, including GPT-40, struggle with the rarest chart category ("others"), indicating the need for more comprehensive dataset coverage. The pattern shifts notably for reasoning questions. The performance gap between GPT-40 and other models shows little correlation with either chart type or performance gap on descriptive questions. Most strikingly, while GPT-40 and GPT-4V show only a 5-point gap on descriptive questions for bar charts, their performance diverges dramatically on reasoning questions, with GPT-40 (45.87) outperforming GPT-4V (22.94) by more than 20 points. Other models consistently underperform on reasoning questions involving bar charts and box plots. We hypothesize that these difficulties stem from challenges in perceiving and estimating values from unannotated visual elements and performing comparative analyses (e.g., sorting, identifying extrema). Further investigation of these specific challenges remains an important direction for future research.

5 Conclusion

Chart understanding is a crucial visual reasoning skill for MLLMs, but our simple stress test reveals that design flaws in existing benchmarks have led to an overestimation of chart understanding capabilities (see §2.2). We introduce CharXiv, a natural, challenging benchmark that pairs charts collected from arXiv papers with human-curated questions and answers. Our results expose clear performance gaps across human, proprietary models and open-source models, and we discuss the broader impacts of our findings in §5.

Limitations. Despite the fact that CharXiv does not require advanced domain-specific knowledge, human accuracy is only 80.5% and 92.1% in reasoning and descriptive questions. We hypothesize that this could be due to issues with automated grading or mistakes by participants in the human evaluation study. However, given the large performance gap between existing MLLMs and humans, we believe that CharXiv is an insightful measurement of chart understanding capabilities. We also note that evaluation benchmarks comprising entirely of examples curated by human experts are expensive to construct and difficult to update and extend. However, as we noted in §2, automatically generated benchmarks often overestimate the capabilities of existing MLLMs.

Broader Impacts.

Chart understanding is an especially crucial skill for MLLMs to develop as they are applied to increasingly difficult real-world tasks, such as reading and summarizing scientific papers. MLLMs with strong chart understanding can analyze and interpret graphs for non-experts to quickly understand and operationalize insights into trends in business, healthcare, and economics. Therefore, faithful benchmarking of MLLMs is important in the identification and rectification of weaknesses in existing MLLMs. Our collection of complex, real-world charts is stylistically representative of the types of data MLLMs need to process. At the time of writing, existing MLLMs struggle to answer chart-related questions reliably, so we believe that CharXiv can meaningfully guide the development and benchmarking of future MLLMs.

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- 1. For all authors...
 - (a) Do the main claims made in the abstract and introduction accurately reflect the paper's contributions and scope? [Yes]
 - All contents are substantiated by sections 2, 3 and 4.
 - (b) Did you describe the limitations of your work? [Yes] We provide limitations in §5.
 - (c) Did you discuss any potential negative societal impacts of your work? [Yes] We provide potential negative societal impacts in §5.
 - (d) Have you read the ethics review guidelines and ensured that your paper conforms to them? [Yes]

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We carefully read the guidelines and ensured that the submission conforms to them.
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- 2. If you are including theoretical results...
 - (a) Did you state the full set of assumptions of all theoretical results? [N/A] We do not have theoretical results.
 - (b) Did you include complete proofs of all theoretical results? [N/A] We do not have theoretical results.
- 3. If you ran experiments (e.g. for benchmarks)...
 - (a) Did you include the code, data, and instructions needed to reproduce the main experimental results (either in the supplemental material or as a URL)? [Yes]
 We include the codebase and link to data in the supplementary material. Instructions to reproduce main experimental results are present in Tab. 15.
 - (b) Did you specify all the training details (e.g., data splits, hyperparameters, how they were chosen)? [N/A]
 We do not train models. We provide splits of the benchmark in §3 and the hyper-

paramters of the evaluations in Tab. 15.
(c) Did you report error bars (e.g., with respect to the random seed after running experiments multiple times)? [N/A]
We use fixed parameters to generate deterministic model responses (whenever possible)

We use fixed parameters to generate deterministic model responses (whenever possible) in our benchmark, which we provide details in Tab. 15.

- (d) Did you include the total amount of compute and the type of resources used (e.g., type of GPUs, internal cluster, or cloud provider)? [N/A]
 We only evaluate the models, so we do not provide information on compute in a separate section. Regardless, all open-source models are evaluated on either a single A100 or H100 GPU from minutes to hours. We use API to evaluate proprietary models.
- 4. If you are using existing assets (e.g., code, data, models) or curating/releasing new assets...
 - (a) If your work uses existing assets, did you cite the creators? [Yes] Our metadata contains information that can be used to trace back to the original assets.
 (b) Did you mention the license of the assets? [Yes]

License for preprints on arXiv server is publicly available online. We provide license information for models we evaluate in Tab. 17.

- (c) Did you include any new assets either in the supplemental material or as a URL? [Yes] We provide 60 samples of our annotated data in App. U and App. V. Our codebase and annotated data can be found in https://charxiv.github.io
- (d) Did you discuss whether and how consent was obtained from people whose data you're using/curating? [No]
 We adhere to applicable license regulations on arXiv. All questions and answers are new assets.
- (e) Did you discuss whether the data you are using/curating contains personally identifiable information or offensive content? [No]
 Every individual chart and question has gone through human inspections and our data do not contain any personally identifiable information or offensive content, except for proper attribution to the source of the charts.
- 5. If you used crowdsourcing or conducted research with human subjects...

- (a) Did you include the full text of instructions given to participants and screenshots, if applicable? [Yes]
 Our general guidelines are elaborated in §3. We provide screenshots of annotations in Apps. R.1, R.2 and R.3
- (b) Did you describe any potential participant risks, with links to Institutional Review Board (IRB) approvals, if applicable? [N/A] We did not recruit external human subjects in our study
- (c) Did you include the estimated hourly wage paid to participants and the total amount spent on participant compensation? [N/A]
 We did not recruit external human subjects in our study

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A Extended Evaluation Results on Validation Set

Table 4: Extended evaluation results on the validation set from Tab. 3. Note that this table includes evaluation result for models (†) after the initial release of CharXiv as well as domain-specific i.e., chart and document multimodal large language models. Cutoff date: October 30, 2024.

	Reasoning Questions Descripti							escriptive	e Questio		
Model	All	Text in Chart	Text in General	Num. in Chart	Num. in General	All	Info. Extr.	Enum.	Patt. Rec.	Cntg.	Comp.
				Baseline	s						
Human	80.50	77.27	77.78	84.91	83.41	92.10	91.40	91.20	95.63	93.38	92.86
Random (GPT-40) [2]	10.80	4.32	39.39	5.60	16.16	19.85	21.65	16.71	23.80	25.70	5.36
	Proprietary Multimodal Large Language Models										
[†] Claude 3.5 Sonnet [5]	60.20	61.14	78.79	63.79	46.72	84.30	82.62	88.86	90.61	90.08	48.66
GPT-40 [2]	47.10	50.00	61.62	47.84	34.50	84.45	82.44	89.18	90.17	85.50	59.82
[†] Gemini 1.5 Pro [78]	43.30	45.68	56.57	45.69	30.57	71.97	81.79	64.73	79.48	76.34	15.18
[†] InternVL V2.0 Pro [12]	39.80	40.00	60.61	44.40	25.76	76.83	77.11	84.67	77.07	78.88	27.23
GPT-4V [2]	37.10	38.18	57.58	37.93	25.33	79.92	78.29	85.79	88.21	80.92	41.07
GPT-40 Mini [2]	34.10	35.23	47.47	32.33	27.95	74.92	74.91	82.81	69.21	79.13	35.71
Claude 3 Sonnet [5]	32.20	31.59	50.51 45.45	31.47	26.20	/3.03	15.14	81.92 60.08	/0.04 64.85	61.83	8.48
Claude 3 Opus [5]	30.20	26.36	50.51	33.62	25.33	71 55	75.62	73 69	73 58	70.48	26 79
Reka Core [73]	28.90	27.50	41.41	28.45	26.64	55.60	58.90	50.52	65.72	71.25	10.71
Reka Flash [73]	26.60	26.59	39.39	30.60	17.03	56.45	61.39	48.59	69.87	72.52	7.14
Qwen VL Max [7]	24.70	26.14	41.41	24.57	14.85	41.48	50.42	28.41	53.71	51.15	4.46
Reka Edge [73]	23.50	20.23	32.32	30.60	18.78	33.65	36.65	28.49	34.72	52.16	4.91
Gemini 1.0 Pro [78]	22.80	20.91	48.48	18.10	20.09	54.37	67.97	39.23	60.48	62.60	8.93
Qwen VL Plus [7]	16.00	15.45	45.45	12.07	8.30	28.93	33.33	17.92	32.10	56.23	2.23
		Open-So	urce Multi	imodal La	rge Languag	ge Models	3				
InternVL V2.0 76B [12]	38.90	40.00	59.60	42.67	24.02	75.17	77.11	78.69	76.20	79.13	32.14
InternVL V2.0 26B [12]	33.40	33.18	<u>51.52</u>	41.81	17.47	62.40	71.35	61.02	55.90	67.94	6.25
Phi-3 Vision [1]	31.60	31.36	46.46	35.78	21.40	60.48	67.62	61.18	54.59	65.39	6.25
CLM 4V OP [24]	29.20	30.00	45.45	32.33	1/.4/	58.50	67.03	52.95	33.00	04.03	5.80
OLM 4 V 9B [24]	29.10	26.14	42.42	33.19	20.06	57.62 62.60	64.20	71 75	45.45	45.04	0.40 5.80
Ovis 1.5 Ulama 3 8B [62]	28.40	20.14	44.44	31.03	17.90	60.15	61 30	68.93	56.33	61.83	7 14
[†] Cambrian 34B [80]	27.30	24.55	44 44	27 59	24.89	59.73	59.31	70.94	53.28	64.63	5 36
[†] MiniCPM-V2.6 [88]	27.10	21.59	45.45	35.34	21.40	61.62	69.28	55.93	60.48	72.01	19.64
MGM HD Yi 34B [49]	25.00	26.59	43.43	27.16	11.79	52.68	53.86	55.04	65.50	53.94	2.23
IXC2 4KHD [17]	25.00	23.86	43.43	29.31	14.85	54.65	61.09	54.08	51.53	59.80	6.70
[†] MiniCPM-V2.5 [31]	24.90	25.23	43.43	25.43	15.72	59.27	62.28	61.90	56.77	68.96	0.27
[†] VILA 1.5 40B [50]	24.00	21.59	41.41	25.00	20.09	38.67	42.88	29.62	51.31	50.89	9.82
LLaVA 1.6 Yi 34B* [55]	22.50	20.45	37.37	23.71	18.78	51.05	46.38	63.44	56.11	51.91	5.80
MGM HD LLaMA3 8B [49]	19.00	19.77	36.36	21.12	/.86	44.42	49.41	39.23	51.09	27.15	1.79
'CogAgent [27]	18.80	16.14	32.32	20.69	14.85	30.30	45.14	20.80	45.25	52.02	5.20
MiniCPM-V2 [31]	18.70	17.95	33 33	19.40	12.23	35.75	39.74	36 56	26.42	44 53	5 36
IDEFICS 2 [41]	18.20	15.45	35.35	17.24	17.03	32.77	36.12	27.28	40.83	43.26	3.12
IDEFICS 2 Chatty [41]	17.80	15.45	34.34	19.83	13.10	41.55	34.88	54.56	45.63	44.27	6.70
MoAI* [42]	17.50	9.32	36.36	21.12	21.40	28.70	31.20	21.23	39.96	40.46	7.59
DeepSeek VL [59]	17.10	16.36	32.32	19.83	9.17	45.80	49.11	45.20	42.79	60.31	4.91
SPHINX V2* [21]	16.10	13.86	28.28	17.67	13.54	30.25	35.59	24.37	41.05	29.52	1.79
LLavA 1.0 Mistral /B* [55]	13.90	11.30	32.32	16.81	/.80	35.40	34.70	33.98	48.91	42.49	8.48
	D	omain-Sj	pecific Mu	ltimodal L	arge Langu	age Mode	els				
[†] DocOwl 1.5 Chat [30]	17.00	14.32	34.34	15.09	16.59	37.40	36.83	49.23	36.68	22.90	3.12
UReader [89]	<u>14.30</u>	11.36	18.18	<u>15.52</u>	<u>17.03</u>	18.98	10.20	27.60	33.41	20.36	5.36
ChartLiama [26]	14.20	8.18	54.34	9.91	21.40	19.23	17.14	12.19	45.89	28.75	6.70
ChartGemma [6/]	12.50	11.59	24.24	10.81	4.80	21.50	27.58	16.97	14.19	19.59	4.40
ChartInstruct ElanT5 [66]	11.70	9.09	21.21	0.04	11.35	15.93	10.43	10.8/	10.57	21.14	∠.08 6 70
[†] DocOw] 1 5 Omni [30]	9.10	5 45	<u>32.32</u> 14.14	9.40 Q 49	13.54	25.70	34.46	17.09	31.894	17 56	4 46
[†] ChartInstruct-Llama2 [66]	8 80	4 09	23 23	7 76	12.66	$\frac{23.70}{21.40}$	23 31	15 50	33 19	27.48	4 91
[†] TinvChart [95]	8.30	5.00	13.13	6.47	14.41	16.15	13.82	14.61	24.67	28.50	3.12
[†] UniChart-ChartQA [65]	5.70	3.41	6.06	3.45	12.23	19.32	9.91	38.26	12.23	19.08	0.45
[†] TextMonkey [58]	3.90	2.50	4.04	3.02	7.42	12.45	12.16	17.92	8.73	6.36	2.68

B Extended Related Works

Multimodal Large Language Models. Multimodal Large Language Models (MLLMs) take inputs beyond text (*e.g.*, image, audio, video, *etc*) and generate text responses [32]. Most MLLMs focus on vision-language tasks. Prototypical approaches train adaptors that connect independent visual-only and language-only modules [45, 44, 4] or adapt language models to visual inputs [32, 11, 10]. With instruction tuning [83] and accessibility to more instruction-tuned Large Language Models [81, 34, 91, 13], there has been a proliferation of open-source MLLMs [56, 96, 100, 90, 14, 43, 40, 51, 8]. More recent work has attempted to scale up the backbone language model, add more alignment data, increase input resolution, design different vision-language adaptation paradigms, and finetune more modules that are otherwise frozen to improve the capabilities of MLLMs [54, 55, 16, 17, 49, 12, 41, 21, 42, 59]. While many recent open-source MLLMs reported on-par or better performance compared to proprietary models in chart understanding [60, 64], little is known about how well these models generalize. In our work, we evaluate the most recent MLLMs on modified versions of chart subsets from MathVista [60] (§2) and CharXiv (§4), showing that open-source models generalize poorly and the performance gap still exists.

MLLM Benchmarks. Prototypical MLLM benchmarks follow Visual Question Answering based on natural images [6, 25, 33, 77, 63] or *screenshots* [22], such as documents [69], diagrams [39], charts [64] and infographics [68]. More recently, several MLLM benchmarks emerged that evaluate multimodal capabilities in a more *knowledge-intensive* [61, 60, 93] and *comprehensive* [92, 57, 20] setting. Chart understanding signifies an important challenge for MLLMs, where the vast majority of open- and proprietary models [2, 5, 73, 7, 78] report model performance on chart understanding tasks [60, 64]. Earliest chart understanding benchmarks often adopt synthetic data and charts [36, 35, 71] or use stylistically consistent charts [64]. More recent chart understanding benchmarks are either not publicly available [53, 86] or widely adopted [85]. CharXiv (§3) is most similar to the design choice of ChartQA [64], yet we adopt more natural, diverse and challenging charts with human-curated QA pairs, resulting in a benchmark that better reflects general capabilities in chart understanding. While chart question-answering is the most common form of evaluating MLLMs, chart understanding capabilities can also be evaluated in terms of chart summarization [72, 101, 38, 74], open-ended generation [37, 29] and generating chart code from textual [87] and visual [76] descriptions.

Specialized Chart Understanding Models. Chart understanding represents an important task for MLLMs, and therefore the research community has been developing models that are specialized for chart understanding to investigate good recipes for training capable models. In particular, MATCHA [52] proposed a training pipeline to incorporate chart deconstruction tasks such as Chart-to-Table and Chart-to-Code as training goals to improve chart understanding. ChartBERT [3] adopted a two-stage pipeline to firstly convert annotated charts to texts, and then use a BERT [15] model to serve as a fact checker for questions. ChartT5 [98] leveraged chart information to fill out the masked content in its corresponding table as a pretraining objective. With the advancement of LLMs, more recent works focus on improving chart understanding from the data perspective. UniChart [65] generates tables from chart data using positional information as well as open-ended QAs and summarizations that are synthetically generated by models and use the data to train chart understanding models. ChartAssistant [70] further enhanced the training data by adding more chart sources, as well as diverse and fine-grained text such as increased number of question templates and Chain-of-Thought [84] answers to train stronger chart understanding MLLMs. ChartLlama [26] and CHOPINLLM [19] proposed an LLM-based pipeline that generates the source table, charts and QAs automatically with GPT models. Finally, ChartGemma [67] finetuned PaliGemma models [9] on chart understanding with their collected WebCharts [66] dataset paired with Gemini-generated instruction tuning data.

C Evaluation Results on Test Set

CharXiv contains 1,000 charts in the validation set and 1,323 charts in the test set. By default, practitioners should evaluate their models on the validation set on their own, and the result is shown in Table 3. Here, we present results on the test set, where ground truth answers are privately held.

Table 5: Model evaluation results on test set. **Bold** number represents the best in-class performance (open-source or proprietary), and <u>underlined</u> number represents the second-place. Models with (*) are those whose performance is constrained by input resolutions (see Tab. 16 for details). Info. Extr.=information extraction, Enum.=enumeration, Patt. Rec.=pattern recognition, Cntg.=counting, Comp.=compositionality. Details for these categories are shown in Fig. 4 and §3.2.

		Rea	soning Qu	iestions			D	escriptive	e Questi	ons	
Model	All	Text in Chart	Text in General	Num. in Chart	Num. in General	All	Info. Extr.	Enum.	Patt. Rec.	Cntg.	Comp.
		Proprie	etary Mult	timodal La	rge Langua	ge Mode	ls				
GPT-40 [2]	47.01	52.15	52.31	47.86	33.98	84.92	84.95	88.02	86.57	88.10	61.99
GPT-4V [2]	33.79	38.25	46.92	27.86	24.92	79.78	78.88	84.83	84.39	82.78	48.83
Claude 3 Sonnet [5]	32.35	33.61	33.85	33.93	27.83	72.75	75.41	81.10	76.95	70.51	11.99
Claude 3 Haiku [5]	30.46	31.46	40.00	28.93	25.89	64.49	68.98	69.84	68.97	61.17	7.89
Claude 3 Opus [5]	28.80	28.31	36.92	29.29	25.89	72.22	76.64	76.04	74.23	68.32	28.36
Reka Core [73]	28.27	30.30	34.62	27.50	22.33	54.76	59.85	49.97	68.24	62.82	10.82
Reka Flash [73]	27.14	29.30	36.92	31.79	14.56	54.72	61.04	46.78	67.70	68.68	9.65
Qwen VL Max [7]	25.17	28.97	41.54	20.00	15.53	40.00	49.50	25.77	56.99	48.17	7.89
Reka Edge [73]	23.89	22.68	42.31	25.00	17.48	31.52	36.27	26.85	31.22	44.32	3.80
Gemini 1.0 Pro [78]	22.68	22.19	39.23	21.43	17.80	51.85	68.48	35.40	62.98	52.38	6.43
Qwen VL Plus [7]	14.89	17.22	33.85	5.36	11.00	27.85	33.90	17.82	30.13	47.99	2.05
Claude 3 Haiku [5] 30.46 31.46 40.00 28.93 23.89 64.49 68.98 69.84 66.97 61.17 7.89 Claude 3 Opus [5] 28.80 28.13 36.92 29.29 25.89 72.22 76.64 76.04 74.23 68.22 28.36 Reka Core [73] 28.27 30.30 34.62 27.50 22.33 54.76 59.85 49.97 68.24 62.22 10.82 Reka Flash [73] 27.14 29.30 36.92 31.79 14.56 54.72 61.04 46.78 67.70 68.68 9.65 Qwen VL Max [7] 25.17 28.97 41.54 20.00 17.48 31.52 36.27 26.85 31.22 48.17 7.89 Reka Edge [73] 23.89 22.68 42.31 25.00 17.48 31.52 36.27 26.85 31.22 44.32 3.80 Gemini 1.0 Pro [78] 22.68 22.19 39.23 21.43 17.80 51.85 68.48 35.40 62.98 52.38 6.43 Qwen VL Plus [7] 14.89											
InternVL Chat V1.5 [12]	28.80	30.63	39.23	31.43	18.45	58.50	72.08	51.84	53.90	59.34	9.94
IXC2 4KHD [17]	24.64	25.99	36.15	28.21	13.92	56.14	65.33	53.94	52.45	58.24	10.53
MGM HD Yi 34B [49]	23.28	27.81	36.15	21.79	10.36	52.66	57.44	54.55	58.80	53.85	1.17
LLaVA 1.6 Yi 34B [55]	20.03	22.52	33.85	16.43	12.62	51.46	49.54	62.25	57.71	47.07	8.19
MGM HD Llama3 8B [49]	19.05	19.70	37.69	22.14	7.12	45.69	54.11	38.29	53.72	53.30	2.63
SPHINX V2 [21]	17.69	15.56	26.15	21.43	14.89	29.59	37.14	22.88	40.65	26.19	1.46
DeepSeek VL [59]	17.38	14.57	33.08	19.64	14.24	45.41	49.54	45.39	46.82	52.38	5.56
IDEFICS 2 [41]	16.70	15.89	28.46	16.79	13.27	31.99	35.17	28.24	39.38	41.21	3.22
IXC2 [16]	16.33	16.39	27.69	18.93	9.06	37.74	36.59	40.04	43.01	48.72	7.89
MiniCPM-V2 [31]	16.10	16.23	28.46	17.86	9.06	34.71	40.05	34.74	23.59	41.21	7.89
LLaVA 1.6 Mistral 7B [55]	16.02	17.05	32.31	13.21	9.71	34.32	37.14	29.62	41.02	47.07	7.89
MoAI [42]	15.42	11.92	29.23	17.14	14.89	28.55	33.90	20.83	37.39	35.53	6.43
IDEFICS 2 Chatty [41]	14.89	15.56	29.23	12.86	9.39	41.04	33.71	55.81	44.10	41.76	10.23

D Evaluation Results by Subject

D.1 Descriptive Question Results on Validation Set

Table 6: Results by subject on descriptive questions. **Bold** number represents best performance in-class (open-source or proprietary). Elec. Eng. & Sys. Sci. denotes Electrical Engineering and Systems Science.

Model	All	Physics	Math	Statistics	Quantitative Biology	Computer Science	Quantitative Finance	Economy	Elec. Eng. Sys. Sci.
	Pro	oprietary N	Iultimod	lal Large	Language N	Aodels			
GPT-40 [2]	84.45	79.92	84.63	85.40	80.56	86.71	85.13	86.23	87.18
GPT-4V [2]	79.92	78.15	79.63	81.19	76.19	77.78	82.33	80.07	84.66
Claude 3 Sonnet [5]	73.65	67.72	73.15	73.01	68.45	75.79	73.92	75.72	81.72
Claude 3 Opus [5]	71.55	65.35	75.00	71.02	65.48	69.25	73.71	71.92	81.09
Claude 3 Haiku [5]	65.08	61.81	68.33	63.27	58.93	62.30	67.89	66.49	71.64
Reka Flash [73]	56.45	51.57	60.37	55.53	52.78	54.56	57.54	57.97	61.13
Reka Core [73]	55.60	50.20	57.96	54.65	51.19	58.93	54.74	55.98	61.13
Gemini 1.0 Pro [78]	54.37	50.98	57.04	52.43	48.02	53.37	55.82	55.98	61.34
Qwen VL Max [7]	41.48	36.81	44.07	43.81	35.32	41.47	42.67	42.39	45.59
Reka Edge [73]	33.65	32.09	38.15	35.40	30.16	32.54	31.03	33.15	36.55
Qwen VL Plus [7]	28.93	23.03	32.41	28.32	25.20	32.54	31.47	27.54	31.09
	Ope	en-Source N	Aultimo	dal Large	Language	Models			
InternVL Chat V1.5 [12]	58.50	53.15	60.56	57.96	54.37	58.13	59.48	59.42	65.13
IXC2 4KHD [17]	54.65	52.17	57.22	55.97	45.83	51.59	56.03	56.52	62.18
MGM HD Yi 34B [49]	52.68	46.46	51.85	54.87	51.19	50.20	55.39	55.07	56.93
LLaVA 1.6 Yi 34B [55]	51.05	48.62	52.22	48.45	44.64	49.01	51.94	55.07	58.19
DeepSeek VL [59]	45.80	42.72	45.74	46.68	42.06	43.25	47.20	46.20	53.15
MGM HD Llama3 8B [49]	44.42	40.75	43.89	45.13	43.45	43.45	45.26	44.02	50.00
IDEFICS 2 Chatty [41]	41.55	36.42	45.00	41.59	41.67	39.68	41.81	41.30	44.96
IXC2 [16]	38.75	36.02	38.89	36.73	36.31	35.52	38.15	44.57	43.28
MiniCPM-V2 [31]	35.77	32.87	42.59	34.07	33.13	33.93	35.13	35.87	38.03
LLaVA 1.6 Mistral 7B [55]	35.40	33.86	38.33	33.85	31.55	33.13	37.28	37.68	37.18
IDEFICS 2 [41]	32.77	30.91	37.04	33.63	28.57	33.53	32.33	28.99	37.61
SPHINX V2 [21]	30.25	28.54	34.07	25.00	27.38	28.37	31.68	29.71	36.97
MoAI [42]	28.70	25.98	31.67	26.99	25.60	27.18	28.45	30.62	32.77

D.2 Reasoning Question Results on Validation Set

Table 7: Results by subject on reasoning questions. **Bold** number represents best performance in-class (open-source or proprietary). Elec. Eng. & Sys. Sci. denotes Electrical Engineering and Systems Science.

Model	All	Physics	Math	Statistics	Quantitative Biology	Computer Science	Quantitative Finance	Economy	Elec. Eng. Sys. Sci.				
	Proprietary Multimodal Large Language Models												
GPT-40 [2]	47.10	53.54	42.96	45.13	46.83	53.97	43.97	43.48	47.06				
GPT-4V [2]	37.10	51.97	39.26	30.09	30.16	34.92	27.59	39.13	42.02				
Claude 3 Sonnet [5]	32.20	37.80	33.33	37.17	30.16	26.19	29.31	31.16	32.77				
Claude 3 Haiku [5]	31.80	37.01	34.07	30.97	29.37	26.19	28.45	30.43	37.82				
Claude 3 Opus [5]	30.20	33.07	36.30	28.32	29.37	25.40	25.86	31.16	31.09				
Reka Core [73]	28.90	28.35	31.11	25.66	28.57	23.81	23.28	34.06	35.29				
Reka Flash [73]	26.60	30.71	27.41	23.01	23.81	20.63	25.00	25.36	36.97				
Qwen VL Max [7]	24.70	25.98	23.70	23.89	26.98	27.78	24.14	21.74	23.53				
Reka Edge [73]	23.50	25.98	27.41	30.09	23.81	19.05	13.79	20.29	27.73				
Gemini 1.0 Pro [78]	22.80	25.20	23.70	23.01	24.60	22.22	13.79	30.43	17.65				
Qwen VL Plus [7]	16.00	22.83	19.26	21.24	10.32	15.08	12.07	13.77	13.45				
	Ope	n-Source N	Iultimo	dal Large	Language	Models							
InternVL Chat V1.5 [12]	29.20	29.92	39.26	30.97	26.98	30.95	22.41	29.71	21.85				
MGM HD Yi 34B [49]	25.00	22.83	29.63	28.32	22.22	26.19	23.28	23.19	24.37				
IXC2 4KHD [17]	25.00	28.35	27.41	22.12	23.02	26.98	18.97	29.71	21.85				
LLaVA 1.6 Yi 34B [55]	22.50	19.69	31.11	23.01	23.81	21.43	18.97	19.57	21.85				
MGM HD Llama3 8B [49]	19.00	20.47	20.00	17.70	18.25	19.84	21.55	16.67	17.65				
IXC2 [16]	18.70	18.90	20.00	17.70	17.46	19.05	19.83	21.74	14.29				
MiniCPM-V2 [31]	18.50	14.96	21.48	17.70	21.43	15.08	20.69	14.49	22.69				
IDEFICS 2 [41]	18.20	19.69	20.74	18.58	16.67	18.25	17.24	15.94	18.49				
IDEFICS 2 Chatty [41]	17.80	17.32	26.67	20.35	14.29	19.84	14.66	15.22	13.45				
MoAI [42]	17.50	21.26	20.00	14.16	19.05	18.25	16.38	17.39	12.61				
DeepSeek VL [59]	17.10	21.26	15.56	26.55	20.63	8.73	11.21	18.12	15.13				
SPHINX V2 [21]	16.10	17.32	21.48	15.93	15.08	13.49	14.66	13.77	16.81				
LLaVA 1.6 Mistral 7B [55]	13.90	17.32	16.30	13.27	12.70	11.11	10.34	14.49	15.13				

E Evaluation Results by Year

E.1 Descriptive Question Results on Validation Set

Table 8: Results by year on descriptive tasks. **Bold** number represents best performance in-class (open-source or proprietary). Elec. Eng. & Sys. Sci. denotes Electrical Engineering and Systems Science.

Model	All	2020	2021	2022	2023					
Proprietary Multi	Proprietary Multimodal Large Language Models									
GPT-40 [2]	84.45	85.53	82.57	85.04	84.78					
GPT-4V [2]	79.92	79.35	78.54	81.25	80.65					
Claude 3 Sonnet [5]	73.65	71.36	73.18	74.90	75.20					
Claude 3 Opus [5]	71.55	71.76	69.35	73.98	71.27					
Claude 3 Haiku [5]	65.08	65.38	63.31	64.86	66.83					
Reka Flash [73]	56.45	58.10	53.35	57.89	56.65					
Reka Core [73]	55.60	57.19	52.68	56.66	56.05					
Gemini 1.0 Pro [78]	54.37	57.39	53.45	51.64	55.04					
Qwen VL Max [7]	41.48	44.74	40.80	40.78	39.62					
Reka Edge [73]	33.65	37.75	30.27	32.27	34.48					
Qwen VL Plus [7]	28.93	29.45	28.45	27.46	30.34					
Open-Source Mult	imodal	Large Lang	guage M	odels						
InternVL Chat V1.5 [12]	58.50	59.21	57.47	58.40	58.97					
IXC2 4KHD [17]	54.65	57.89	52.68	53.89	54.23					
MGM HD Yi 34B [49]	52.68	54.15	49.33	53.18	54.23					
LLaVA 1.6 Yi 34B [55]	51.05	50.91	50.77	51.64	50.91					
DeepSeek VL [59]	45.80	47.77	43.01	47.54	45.06					
MGM HD Llama3 8B [49]	44.42	45.75	43.97	44.06	43.95					
IDEFICS 2 Chatty [41]	41.55	43.52	40.04	39.14	43.55					
IXC2 [16]	38.75	39.68	36.40	38.63	40.42					
MiniCPM-V2 [31]	35.77	37.96	34.58	35.04	35.58					
LLaVA 1.6 Mistral 7B [55]	35.40	36.94	34.48	37.09	33.17					
IDEFICS 2 [41]	32.77	35.32	31.23	30.02	34.58					
SPHINX V2 [21]	30.25	32.19	30.75	27.25	30.75					
MoAI [42]	28.70	31.88	25.29	27.36	30.44					

E.2 Reasoning Task Results on Validation Set

Table 9: Results by year on reasoning questions. Bold number represents best performance in-class (open-source or proprietary).

Model	All	2020	2021	2022	2023					
Proprietary Multimodal Large Language Models										
GPT-40 [2]	47.10	43.32	49.04	45.49	50.40					
GPT-4V [2]	37.10	33.60	39.46	37.30	37.90					
Claude 3 Sonnet [5]	32.20	31.98	33.33	27.46	35.89					
Claude 3 Haiku [5]	31.80	31.58	34.10	30.33	31.05					
Claude 3 Opus [5]	30.20	29.15	31.42	30.74	29.44					
Reka Core [73]	28.90	27.94	31.80	29.51	26.21					
Reka Flash [73]	26.60	26.32	27.59	25.82	26.61					
Qwen VL Max [7]	24.70	27.94	24.90	23.36	22.58					
Reka Edge [73]	23.50	23.08	26.44	22.13	22.18					
Gemini 1.0 Pro [78]	22.80	21.86	22.99	24.59	21.77					
Qwen VL Plus [7]	16.00	15.38	14.94	16.80	16.94					
Open-Source Mult	timodal 1	Large Lang	guage M	odels						
InternVL Chat V1.5 [12]	29.20	31.17	31.42	27.05	27.02					
MGM HD Yi 34B [49]	25.00	25.51	24.90	24.18	25.40					
IXC2 4KHD [17]	25.00	23.08	28.35	23.77	24.60					
LLaVA 1.6 Yi 34B [55]	22.50	20.65	26.05	21.31	21.77					
MGM HD Llama3 8B [49]	19.00	17.81	17.62	20.49	20.16					
IXC2 [16]	18.70	18.22	17.62	15.57	23.39					
MiniCPM-V2 [31]	18.50	15.79	19.54	23.77	14.92					
IDEFICS 2 [41]	18.20	21.46	15.71	16.80	18.95					
IDEFICS 2 Chatty [41]	17.80	19.84	16.86	16.80	17.74					
MoAI [42]	17.50	16.60	16.86	15.16	21.37					
DeepSeek VL [59]	17.10	18.62	17.62	16.80	15.32					
SPHINX V2 [21]	16.10	17.00	18.39	12.70	16.13					
LLaVA 1.6 Mistral 7B [55]	13.90	11.34	12.26	19.26	12.90					

F Descriptive Question Results by Question Number on Validation Set

Table 10: Model evaluation results by question number (Q1–Q9) on descriptive questions. **Bold** number represents best performance in-class (open-source or proprietary). We provide the mapping from question numbers to contents in Tab. 20.

Model	All	Q1	Q2	Q3	Q4	Q5	Q6	Q7	Q8	Q9	
Proprietary Multimodal Large Language Models											
GPT-40 [2]	84.45	76.23	84.78	73.82	87.94	86.61	84.34	82.91	89.29	77.11	
GPT-4V [2]	79.92	81.56	82.17	70.82	82.10	83.26	73.09	74.79	87.50	72.64	
Claude 3 Sonnet [5]	73.65	74.18	76.09	53.22	88.33	84.94	76.71	75.21	87.05	77.11	
Claude 3 Opus [5]	71.55	68.03	75.22	60.09	87.94	84.52	78.31	73.93	85.27	74.13	
Claude 3 Haiku [5]	65.08	59.84	75.65	51.07	85.60	76.15	68.27	71.37	76.79	60.20	
Reka Flash [73]	56.45	67.62	67.83	63.95	62.26	63.60	45.78	59.40	64.29	60.20	
Reka Core [73]	55.60	50.41	66.52	57.51	62.65	66.53	50.20	58.97	68.75	63.68	
Gemini 1.0 Pro [78]	54.37	64.34	76.09	63.95	75.49	79.50	55.82	60.68	56.25	60.70	
Qwen VL Max [7]	41.48	39.75	67.83	59.23	63.81	58.58	25.70	38.89	43.30	33.33	
Reka Edge [73]	33.65	19.26	53.91	37.34	49.03	43.10	26.10	28.21	45.98	30.85	
Qwen VL Plus [7]	28.93	25.00	59.13	44.64	39.30	27.62	19.28	19.66	24.55	16.92	
	Open-S	ource Mu	ltimoda	l Large l	Languag	e Model	s				
InternVL Chat V1.5 [12]	58.50	73.36	73.91	59.66	77.43	77.82	60.24	64.53	73.66	63.18	
IXC2 4KHD [17]	54.65	68.03	70.87	43.35	73.15	70.29	44.58	56.84	55.80	49.25	
MGM HD Yi 34B [49]	52.68	61.07	61.74	33.48	64.59	64.44	41.77	49.15	68.30	54.73	
LLaVA 1.6 Yi 34B [55]	51.05	66.39	46.52	26.18	54.86	58.58	34.54	36.32	60.27	38.81	
DeepSeek VL [59]	45.80	61.89	54.35	33.48	59.14	51.05	38.96	44.02	55.36	47.76	
MGM HD Llama3 8B [49]	44.42	41.39	56.96	35.62	63.42	61.09	40.16	46.58	48.21	31.34	
IDEFICS 2 Chatty [41]	41.55	20.49	52.61	33.91	37.35	41.42	30.12	29.06	26.34	24.38	
IXC2 [16]	38.75	60.66	35.65	16.31	33.46	46.86	22.09	23.08	31.70	27.86	
MiniCPM-V2 [31]	35.77	47.95	41.74	39.06	44.36	45.61	30.12	29.06	18.30	26.37	
LLaVA 1.6 Mistral 7B [55]	35.40	56.56	46.52	16.74	38.52	37.24	22.09	24.79	42.41	35.82	
IDEFICS 2 [41]	32.77	36.48	48.26	40.77	33.46	40.17	29.72	24.79	33.93	30.85	
SPHINX V2 [21]	30.25	53.69	36.96	16.31	43.19	35.98	36.14	25.21	12.50	13.93	
MoAI [42]	28.70	52.05	32.61	11.59	31.91	47.70	20.88	20.94	24.55	22.39	

Table 11: Model evaluation results by question number (Q10–Q19) on descriptive questions. **Bold** number represents best performance in-class (open-source or proprietary). We provide the mapping from question numbers to contents in Tab. 20.

Model	All	Q10	Q11	Q12	Q13	Q14	Q15	Q16	Q17	Q18	Q19
Proprietary Multimodal Large Language Models											
GPT-40 [2]	84.45	84.25	83.43	83.52	85.39	93.26	95.85	86.11	59.82	95.55	93.85
GPT-4V [2]	79.92	79.45	84.00	79.67	79.91	90.07	93.29	72.22	41.07	93.52	87.69
Claude 3 Sonnet [5]	73.65	65.07	66.86	75.82	69.41	84.40	87.86	55.56	8.48	86.64	78.46
Claude 3 Opus [5]	71.55	62.33	54.86	71.98	62.56	77.66	69.33	41.67	26.79	91.50	84.62
Claude 3 Haiku [5]	65.08	58.22	54.29	66.48	65.30	60.99	82.75	58.33	8.04	73.28	56.92
Reka Flash [73]	56.45	76.03	67.43	67.03	68.04	40.43	23.64	75.00	7.14	70.85	80.00
Reka Core [73]	55.60	66.44	58.29	69.23	57.99	36.52	36.42	66.67	10.71	70.85	87.69
Gemini 1.0 Pro [78]	54.37	64.38	44.00	53.30	57.99	9.57	26.84	41.67	8.93	74.90	84.62
Qwen VL Max [7]	41.48	39.04	46.29	50.55	49.77	10.28	15.97	50.00	4.46	59.51	80.00
Reka Edge [73]	33.65	52.05	39.43	49.45	42.47	24.82	7.99	36.11	4.91	31.17	60.00
Qwen VL Plus [7]	28.93	52.74	36.00	58.79	41.55	7.80	6.39	33.33	2.23	29.15	56.92
	OI	pen-Source	Multim	odal La	rge Lang	guage M	odels				
InternVL Chat V1.5 [12]	58.50	54.79	34.29	69.23	67.58	27.30	44.41	58.33	5.80	65.59	73.85
IXC2 4KHD [17]	54.65	52.05	44.00	62.09	51.14	71.28	42.49	66.67	6.70	54.66	70.77
MGM HD Yi 34B [49]	52.68	56.85	78.29	46.15	51.14	64.18	40.26	50.00	2.23	58.70	69.23
LLaVA 1.6 Yi 34B [55]	51.05	58.90	54.86	36.81	36.99	80.85	84.35	50.00	5.80	57.89	78.46
DeepSeek VL [59]	45.80	53.42	41.14	57.14	42.47	60.28	24.60	47.22	4.91	43.32	84.62
MGM HD Llama3 8B [49]	44.42	58.90	53.71	50.00	49.32	39.01	30.99	47.22	1.79	49.80	66.15
IDEFICS 2 Chatty [41]	41.55	39.73	46.29	39.56	30.59	82.62	85.62	22.22	6.70	48.58	67.69
IXC2 [16]	38.75	48.63	52.57	52.20	37.44	51.42	59.42	33.33	5.80	44.53	64.62
MiniCPM-V2 [31]	35.77	42.47	25.14	42.31	43.38	47.16	41.85	36.11	5.36	25.91	55.38
LLaVA 1.6 Mistral 7B [55]	35.40	42.47	49.71	43.41	32.42	42.91	19.81	50.00	8.48	48.18	40.00
IDEFICS 2 [41]	32.77	37.67	22.86	41.76	33.33	28.01	15.34	30.56	3.12	55.06	60.00
SPHINX V2 [21]	30.25	22.60	46.86	24.73	36.07	21.28	34.19	30.56	1.79	38.46	58.46
MoAI [42]	28.70	34.25	38.29	34.62	30.59	22.70	10.22	30.56	7.59	42.51	70.77

G Evaluation Results without Unanswerable Descriptive Questions

To assess whether models tend to hallucinate on unanswerable cases or falsely admit "Not Applicable" or fail to provide the correct answer for answerable cases, we report models' performance on descriptive questions of the validation set on CharXiv *without* considering unanswerable questions.

As shown in Tab. 12, we observe that all proprietary models except the top 3 have improved performance (indicated by a positive Δ) when unanswerable questions are not taken into account, while the vast majority of open-source models have performance degradation (indicated by a negative Δ) when unanswerable questions are not taken into account. A possible explanation is that proprietary models tend to be overconfident on the answerability of a descriptive question, while open-source models tend to be conservative. We leave a more rigorous explanation on this aspect for future work.

Table 12: Results without considering unanswerable questions on **descriptive** questions of the validation split. **Bold** number represents best performance in-class (open-source or proprietary). Δ represents performance difference of evaluations without considering unanswerable questions compared to evaluations considering both answerable and unanswerable questions, the latter of which is reported in Tab. 3. Note that all questions in the Comp. category are answerable, so the difference is 0 for all models.

Model	All	Δ	Info. Extr.	Δ	Enum.	Δ	Patt. Rec.	Δ	Cntg.	Δ	Comp.	Δ
Proprietary Multimodal Large Language Models												
GPT-40 [2]	82.77	-1.68	83.28	0.84	83.14	-6.04	84.71	-0.79	92.11	1.94	59.82	0.00
GPT-4V [2]	75.73	-4.19	77.61	-0.68	75.46	-10.33	77.71	-3.21	87.63	-0.58	41.07	0.00
Claude 3 Sonnet [5]	70.53	-3.12	76.13	0.39	72.29	-9.63	74.20	1.94	79.47	2.83	8.48	0.00
Claude 3 Haiku [5]	65.33	0.25	72.22	2.35	69.45	-0.53	59.87	-1.96	70.26	5.41	8.04	0.00
Claude 3 Opus [5]	73.93	2.38	78.69	3.07	76.46	2.77	70.38	-0.10	82.11	8.53	26.79	0.00
Reka Core [73]	60.03	4.43	61.56	2.66	62.94	12.42	70.38	-0.87	70.00	4.28	10.71	0.00
Reka Flash [73]	59.00	2.55	60.49	-0.90	60.43	11.84	70.70	-1.82	71.84	1.97	7.14	0.00
Qwen VL Max [7]	50.50	9.02	54.15	3.73	45.91	17.50	63.69	12.54	59.74	6.03	4.46	0.00
Reka Edge [73]	36.53	2.93	41.00	4.35	32.05	3.72	51.27	-0.89	32.63	-2.09	4.91	0.00
Gemini 1.0 Pro [78]	62.40	8.02	68.37	0.40	58.76	19.53	70.06	7.46	70.00	9.52	8.93	0.00
Qwen VL Plus [7]	34.73	5.80	36.68	3.35	27.05	9.13	58.60	2.37	38.68	6.58	2.23	0.00
Open-Source Multimodal Large Language Models												
InternVL Chat V1.5 [12]	63.07	4.57	68.37	-1.26	68.78	15.83	68.15	3.52	62.89	9.83	5.80	0.00
MGM HD Yi 34B [49]	51.30	-1.35	53.61	-0.25	55.26	0.30	56.69	2.75	60.53	-4.97	2.23	0.00
IXC2 4KHD [17]	54.83	0.18	60.08	-1.01	53.42	-0.66	62.74	2.94	58.42	6.89	6.70	0.00
LLaVA 1.6 Yi 34B [55]	39.53	-11.52	39.99	-6.39	37.40	-26.04	42.04	-9.87	58.95	2.84	5.80	0.00
MGM HD Llama3 8B [49]	44.23	-0.10	50.78	1.37	33.56	-5.34	53.18	-2.80	53.16	2.07	1.79	0.00
IXC2 [16]	29.70	-9.00	27.51	-6.59	26.04	-17.38	50.00	-2.93	41.32	-5.40	5.80	0.00
MiniCPM-V2 [31]	29.23	-6.25	35.94	-3.80	13.52	-22.07	43.95	-0.58	29.74	3.32	5.36	0.00
IDEFICS 2 [41]	35.07	2.30	36.48	0.36	28.71	1.43	46.82	3.56	48.68	7.85	3.12	0.00
IDEFICS 2 Chatty [41]	29.63	-11.92	37.69	2.81	10.68	-43.88	35.99	-8.28	36.32	-9.31	6.70	0.00
MoAI [42]	27.57	-1.11	26.90	-4.30	21.20	0.05	42.04	1.58	40.00	0.04	7.59	0.00
DeepSeek VL [59]	45.17	-0.60	48.01	-1.04	41.90	-3.30	59.55	-0.76	51.05	8.26	4.91	0.00
SPHINX V2 [21]	26.27	-3.91	30.07	-5.52	14.52	-9.61	23.57	-5.95	46.58	5.53	1.79	0.00
LLaVA 1.6 Mistral 7B [55]	29.77	-5.46	30.28	-4.24	26.54	-7.12	33.76	-8.73	42.11	-6.80	8.48	0.00

H Evaluation Results by Chart Type

H.1 Descriptive Question Results on Validation Set

We include model performance for the top 9 most common chart types. "Others" indicate chart types that are not from the top 9 most common types. Note that each chart can contribute to the statistics of multiple chart types when the chart is composed of multiple applicable chart types.

Table 13: Results by chart types on **descriptive** questions. **Bold** number represents best performance in-class (open-source or proprietary).

Model	Line Chart	Scatter Plot	Bar Chart	Others	Heat- map	Area Chart	Box Plot	Histo- gram	Density Plot	Contour Plot
Question Count	2160	752	436	636	436	224	176	208	160	108
	Pro	prietary I	Multimo	dal Large	e Langua	age Mod	els			
GPT-40 [2]	85.83	80.85	82.57	77.04	82.57	83.04	82.95	82.21	80.00	84.26
GPT-4V [2]	81.57	78.06	77.52	75.16	74.08	77.68	77.84	78.85	78.75	69.44
Claude 3 Sonnet [5]	77.78	71.94	72.48	65.88	61.93	74.55	72.16	75.00	73.12	58.33
Claude 3 Opus [5]	74.95	70.21	72.02	62.89	56.19	72.32	67.61	74.52	77.50	60.19
Claude 3 Haiku [5]	70.14	62.37	58.94	56.13	57.57	68.30	55.68	65.38	64.38	59.26
Reka Flash [73]	56.48	53.86	52.29	52.52	52.98	53.12	51.70	53.37	53.12	50.93
Reka Core [73]	55.93	54.12	58.49	47.33	50.23	51.79	53.41	54.81	55.00	48.15
Gemini 1.0 Pro [78]	54.86	52.79	49.54	52.52	50.92	53.12	50.00	54.33	56.25	52.78
Qwen VL Max [7]	42.64	37.37	41.97	35.06	38.30	37.50	38.07	33.17	40.00	29.63
Reka Edge [73]	35.37	31.91	30.50	28.30	30.73	33.93	25.57	34.13	36.88	26.85
Qwen VL Plus [7]	30.32	27.13	27.52	25.63	22.48	28.57	28.41	30.77	30.00	23.15
	Oper	n-Source	Multimo	dal Larg	e Langu	age Mod	lels			
InternVL Chat V1.5 [12]	60.79	54.92	56.19	53.14	47.25	62.05	55.68	62.50	60.62	55.56
IXC2 4KHD [17]	61.02	53.06	46.33	44.18	45.64	59.38	52.84	55.29	54.38	45.37
MGM HD Yi 34B [49]	55.42	49.20	50.46	46.86	45.64	51.34	44.32	53.37	53.75	42.59
LLaVA 1.6 Yi 34B [55]	55.05	48.67	44.50	45.75	41.74	53.57	43.75	49.52	46.25	37.96
DeepSeek VL [59]	49.26	42.95	40.14	36.79	37.61	44.20	39.20	44.23	46.88	35.19
MGM HD Llama3 8B [49]	45.42	39.63	44.50	42.77	40.83	47.32	39.77	43.75	45.00	39.81
IDEFICS 2 Chatty [41]	42.55	39.76	38.30	38.21	37.16	45.09	35.80	42.31	43.75	41.67
IXC2 [16]	41.57	36.17	34.86	37.89	33.49	40.62	36.36	37.02	40.00	34.26
MiniCPM-V2 [31]	39.21	31.78	28.90	30.82	24.08	36.61	25.00	34.13	35.62	33.33
LLaVA 1.6 Mistral 7B [55]	35.09	30.72	33.94	36.48	37.16	36.16	27.27	27.88	28.75	31.48
IDEFICS 2 [41]	33.89	30.85	27.29	30.50	27.52	33.04	28.41	28.85	31.25	25.00
SPHINX V2 [21]	32.41	28.72	26.38	28.93	22.48	29.46	26.14	25.96	30.62	20.37
MoAI [42]	28.89	25.80	23.39	30.97	27.52	25.89	30.11	25.00	34.38	26.85

H.2 Reasoning Question Results on Validation Set

Table 14: Results by chart types on **reasoning** questions. **Bold** number represents best performance in-class (open-source or proprietary).

Model	Line Chart	Scatter Plot	Bar Chart	Others	Heat- map	Area Chart	Box Plot	Histo- gram	Density Plot	Contour Plot
Question Count	540	188	109	159	109	56	44	52	40	27
	Pro	prietary l	Multimo	dal Large	e Langua	age Mod	els			
GPT-40 [2]	45.93	39.89	45.87	50.94	51.38	48.21	38.64	51.92	55.00	51.85
GPT-4V [2]	39.81	30.32	22.94	36.48	41.28	42.86	27.27	40.38	35.00	44.44
Claude 3 Sonnet [5]	33.15	27.66	18.35	33.33	33.03	35.71	31.82	26.92	35.00	25.93
Claude 3 Haiku [5]	34.44	26.06	17.43	39.62	29.36	26.79	27.27	34.62	37.50	22.22
Claude 3 Opus [5]	29.44	22.87	22.94	34.59	41.28	32.14	22.73	28.85	32.50	29.63
Reka Core [73]	28.89	21.81	22.94	30.82	31.19	23.21	25.00	34.62	35.00	37.04
Reka Flash [73]	25.74	21.28	20.18	26.42	26.61	25.00	27.27	21.15	27.50	14.81
Qwen VL Max [7]	25.56	22.34	18.35	22.01	24.77	21.43	25.00	25.00	22.50	29.63
Reka Edge [73]	23.33	18.62	17.43	23.90	22.94	17.86	20.45	32.69	35.00	29.63
Gemini 1.0 Pro [78]	23.70	23.94	16.51	26.42	15.60	26.79	13.64	26.92	30.00	25.93
Qwen VL Plus [7]	16.11	12.23	8.26	16.35	21.10	17.86	13.64	11.54	17.50	18.52
	Oper	n-Source	Multimo	odal Larg	e Langu	age Mod	lels			
InternVL Chat V1.5 [12]	29.63	27.13	21.10	25.16	26.61	28.57	20.45	30.77	37.50	33.33
MGM HD Yi 34B [49]	25.74	21.81	22.02	22.64	18.35	17.86	15.91	28.85	32.50	29.63
IXC2 4KHD [17]	25.00	20.74	23.85	25.16	23.85	21.43	20.45	28.85	30.00	18.52
LLaVA 1.6 Yi 34B [55]	23.33	18.09	22.02	18.87	19.27	17.86	22.73	17.31	30.00	22.22
MGM HD Llama3 8B [49]	19.07	15.43	14.68	19.50	20.18	17.86	18.18	19.23	22.50	3.70
IXC2 [16]	15.56	14.89	18.35	15.09	29.36	12.50	18.18	13.46	15.00	18.52
MiniCPM-V2 [31]	20.37	17.02	10.09	20.75	13.76	21.43	9.09	13.46	20.00	14.81
IDEFICS 2 [41]	18.15	17.02	15.60	19.50	15.60	14.29	11.36	13.46	7.50	14.81
IDEFICS 2 Chatty [41]	16.85	12.77	16.51	20.75	18.35	17.86	15.91	17.31	10.00	18.52
MoAI [42]	15.37	15.96	13.76	16.98	27.52	16.07	9.09	11.54	20.00	11.11
DeepSeek VL [59]	16.30	16.49	14.68	15.09	18.35	16.07	15.91	19.23	17.50	18.52
SPHINX V2 [21]	17.59	13.83	11.01	11.95	17.43	14.29	6.82	17.31	12.50	18.52
LLaVA 1.6 Mistral 7B [55]	14.07	11.70	11.93	11.95	13.76	10.71	6.82	15.38	12.50	11.11



I Relationship Between Response Length and Correctness

Figure 7: Relationship between models' generation length and correctness on reasoning questions. We use GPT-40 tokenizer to calculate the lengths of model responses to reasoning questions in CharXiv. The color encoding considers applicable data points from its corresponding bin and the proceeding and following 2 bins.

J Run Configurations

For evaluation configurations on more recent models (i.e., from Tab. 3), refer to the leaderboard (by clicking the model's name).

Table 15: Run configurations for all models. Unset values indicate that their default values are being used. For Qwen models, we are unable to use a Top-P of exactly 1 due to their API settings, and we end up using a value of 0.99999. Temp. denotes temperature. We use model pages' code to set up the run configurations whenever possible.

Model	Do Sample	Max New Tokens	Temp.	Top-P	Seed	
	Proprietary Multimodal Large Language	e Models				
GPT-40 [2]	gpt-40-2024-05-13		1000	0	1	42
GPT-4V [2]	gpt-4-turbo-2024-04-09		1000	0	1	42
Claude 3 Sonnet [5]	claude-3-sonnet-20240229		1024	0	1	
Claude 3 Opus [5]	claude-3-opus-20240229		1024	0	1	
Claude 3 Haiku [5]	claude-3-haiku-20240307		1024	0	1	
Reka Flash [73]	reka-flash-20240226		1024	0	1	
Reka Core [73]	reka-core-20240415		1024	0	1	
Gemini 1.0 Pro [78]	gemini-1.0-pro-vision-001		1000	0	1	
Qwen VL Max [7]	qwen-vl-max			0	1*	42
Reka Edge [73]	reka-edge-20240208		1024	0	1	
Qwen VL Plus [7]	qwen-vl-plus			0	1*	42
	Open-Source Multimodal Large Languag	e Models				
InternVL Chat V1.5 [12]	OpenGVLab/InternVL-Chat-V1-5	False	512			
IXC2 4KHD [17]	internlm/internlm-xcomposer2-4khd-7b	False				
MGM HD Yi 34B [49]	YanweiLi/MGM-34B-HD	False	1024	0	1	
LLaVA 1.6 Yi 34B [55]	llava-hf/llava-v1.6-34b-hf	False	100			
DeepSeek VL [59]	deepseek-ai/deepseek-vl-7b-chat	False	512			
MGM HD Llama3 8B [49]	YanweiLi/MGM-8B-HD	False	1024	0	1	
IDEFICS 2 Chatty [41]	HuggingFaceM4/idefics2-8b-chatty	False	500			
IXC2 [16]	internlm/internlm-xcomposer2-v1-7b	False				
MiniCPM-V2 [31]	openbmb/MiniCPM-V-2	False		0	1	
LLaVA 1.6 Mistral 7B [55]	llava-hf/llava-v1.6-mistral-7b-hf	False	1000			
IDEFICS 2 [41]	HuggingFaceM4/idefics2-8b	False	500			
SPHINX V2 [21]	Alpha-VLLM/LLaMA2-Accessory		1024	0	1	42
MoAI [42]	BK-Lee/MoAI-7B	False				

K Open-Source Model Components

Table 16: We summarize the visual and language model components of the open-source models evaluated in CharXiv. In addition, we provide the input resolution that is used in our evaluation. Note that LLaVA 1.6 models support dynamic aspect ratio input resolution, so the actual resolution may not necessarily be 672×672 . MoAI uses additional vision encoders as verbalizers. Charts in CharXiv have an average size of 996×702 and the max size of 1024×1024 .

Model	Vision Encoder	Language Model	Resolu- tion
InternVL Chat v1.5 [12]	InternViT-6B-448px-V1-5	InternLM2-Chat-20B	1344×1344
IXC2 4KHD [17]	CLIP ViT-L-14-336	InternLM2-7B-ChatSFT	1344×1344
MGM HD Yi 34B [49]	CLIP ViT-L-14-336 & OpenCLIP ConvNeXt-L	Nous-Hermes-2-Yi-34B	1536×1536
LLaVA 1.6 Yi 34B [55]	CLIP ViT-L-14-336	Nous-Hermes-2-Yi-34B	$672 \times 672^*$
DeepSeek VL [59]	SigLIP-384-SO400M & SAM-ViT-Base	DeepSeek-LLM-7B	1024×1024
MGM HD Llama3 8B [49]	CLIP ViT-L-14-336 & OpenCLIP ConvNeXt-L	LLaMA-3-8B-Instruct	1536×1536
IDEFICS 2 Chatty [41]	SigLIP-384-SO400M	Mistral-7B	980×980
IXC2 [16]	CLIP ViT-L-14-336	InternLM-7B	490×490
MiniCPM-V2 [31]	SigLIP-384-SO400M	MiniCPM-2.4B	1344×1344
LLaVA 1.6 Mistral 7B [55]	CLIP ViT-L-14-336	Mistral-7B	$672\times672^{\ast}$
IDEFICS 2 [41]	SigLIP-384-SO400M	Mistral-7B	980×980
SPHINX V2 [21]	DINOv2 VIT-g14 & OpenCLIP ConvNeXt-XXL	LLaMA2-13B	448×448
MoAI [42]	CLIP ViT-L-14-336*	InternLM-7B	490×490

L Model License

Name	Model License	Code License
GPT-40	Proprietary	Proprietary
GPT-4V	Proprietary	Proprietary
Claude 3 Sonnet	Proprietary	Proprietary
Claude 3 Haiku	Proprietary	Proprietary
Claude 3 Opus	Proprietary	Proprietary
Reka Core	Proprietary	Proprietary
Reka Flash	Proprietary	Proprietary
Qwen VL Max	Proprietary	Proprietary
Reka Edge	Proprietary	Proprietary
Gemini 1.0 Pro	Proprietary	Proprietary
Qwen VL Plus	Proprietary	Proprietary
InternVL Chat V1.5	MIT	MIT
IXC2 4KHD	Custom	Apache 2.0
MGM HD Yi 34B	Apache 2.0	Apache 2.0
LLaVA 1.6 Yi 34B	Apache 2.0	Apache 2.0
MGM HD Llama3 8B	llama3	Apache 2.0
SPHINX V2	llama2	Not Applicable
DeepSeek VL	deepseek	MIT
IDEFICS 2	Apache 2.0	Not Applicable
IXC2	Custom	Apache-2.0
MiniCPM-V2	minicpm	Apache 2.0
LLaVA 1.6 Mistral 7B	Apache 2.0	Apache 2.0
MoAI	Apache 2.0	Apache 2.0
IDEFICS 2 Chatty	Apache 2.0	Not Applicable

Table 17: Summary of licenses in models that are evaluated in CharXiv. Entries marked with "Not Applicable" indicate that authors do not have an explicit code license displayed within the codebase or model checkpoint page.

M Evaluations on Automatic Grading

To further validate the feasibility of automatic grading, we performed human grading for a total of 400 questions across descriptive and reasoning tasks on 4 different models. Overall, human grading and GPT-40 based automatic grading match 98.5% of the time. Moreover, by looking at the matching rate on different models, we do not find any significant favoritism in grading for certain models. We provide detailed statistics in Tab. 18 and Tab. 19. (A), (B), (C), (D) refer to GPT-40 [2], Claude 3 Sonnet [5], InternVL Chat V1.5 [16], and MGM HD Yi 34B [49] respectively. TP: both human and GPT-40 rate the response as correct. FP: human rates the response as incorrect. TN: both human and GPT-40 rate the response as incorrect. F1: the corresponding F1 score.

	(A)	(B)	(C)	(D)
TP	39	36	28	21
FP	1	0	1	0
FN	0	0	1	0
TN	10	14	20	29
F1	0.99	1.00	0.97	1.00

Table 18: Descriptive Questions

	(A)	(B)	(C)	(D)
TP	24	14	18	14
FP	0	1	0	0
FN	1	1	0	0
TN	25	34	32	36
F1	0.98	0.93	1.00	1.00

Table 19: Reasoning Questions

N Visualization of Sample Charts

We sample 30 charts from different evaluation suite and visualize the charts used to evaluate models.



(a) **FigureQA** consists of 4 types of chart (scatter, line, bar, pie).



(c) **PlotQA** consists of 3 types of chart (scatter, line, bar).



(b) DVQA consists of only bar chart.



(d) **ChartQA** consists of 3 types of chart (line, bar, pie).



(e) **CharXiv** consists of handpicked figures that visually illustrate data as a chart sourced from arXiv preprints with *unbounded* chart types.



O Prompts for Descriptive Questions

O.1 Response Generation

Table 20: Instructions for descriptive questions. We construct the query by prepending the subplot prefix (*e.g., for the subplot at row M and column N*) before the question when there are multiple subplots, and appending its corresponding instruction after the question.

QID	Category	Question	Instructions
1	Information Extraction	What is its title?	 * Your final answer should be the most relevant title of the plot that is explicitly written. * If the plot does not have an explicit title or contains only a letter, answer 'Not Applicable'.
2	Information Extraction	What is the label of the x-axis?	* Your final answer should be the label of the x-axis that is explicitly written, including the case when x-axis is shared across multiple subplots. When the x-axis is present on both the top and bottom of the plot, answer the label of the x-axis at the bottom. * If the plot does not have an explicit x-axis label, an- swer 'Not Applicable'.
3	Information Extraction	What is the label of the y-axis?	* Your final answer should be the label of the y-axis that is explicitly written, including the case when y-axis is shared across multiple subplots. When the y-axis is present on both the left and right of the plot, answer the label of the y-axis at the left. * If the plot does not have an explicit y-axis label, an- swer 'Not Applicable'.
4	Information Extraction	What is the leftmost la- beled tick on the x-axis?	* Your final answer should be the tick value on the x- axis that is explicitly written, including the case when x-axis is shared across multiple subplots. When the x-axis is present on both the top and bottom of the plot, answer based on the axis at the bottom. Ignore units or scales that are written separately from the tick, such as units and scales from the axis label or the corner of the plot.
5	Information Extraction	What is the rightmost labeled tick on the x-axis?	* Your final answer should be the tick value on the x- axis that is explicitly written, including the case when x-axis is shared across multiple subplots. When the x-axis is present on both the top and bottom of the plot, answer based on the axis at the bottom. Ignore units or scales that are written separately from the tick, such as units and scales from the axis label or the corner of the plot.
6	Information Extraction	What is the spatially lowest labeled tick on the y-axis?	* Your final answer should be the tick value on the y- axis that is explicitly written, including the case when y-axis is shared across multiple subplots. When the y-axis is present on both the left and right of the plot, answer based on the axis at the left. Ignore units or scales that are written separately from the tick, such as units and scales from the axis label or the corner of the plot.
QID	Category	Question	Instructions
-----	---------------------------	---	---
7	Information Extraction	What is the spatially high- est labeled tick on the y-axis?	* Your final answer should be the tick value on the y- axis that is explicitly written, including the case when y-axis is shared across multiple subplots. When the y-axis is present on both the left and right of the plot, answer based on the axis at the left. Ignore units or scales that are written separately from the tick, such as units and scales from the axis label or the corner of the plot.
8	Enumeration	What is difference between consecutive numerical tick values on the x-axis?	* Your final answer should be the difference between consecutive numerical tick values of the x-axis, includ- ing the case when x-axis is shared across multiple sub- plots. When the x-axis is present on both the top and bottom of the plot, answer based on the axis at the bot- tom. Ignore units or scales that are written separately from the tick, such as units and scales from the axis label or the corner of the plot. * If the plot does not have an explicit x-axis tick value, or if the tick values are not numerical, or if the difference is not constant between all consecutive tick values, answer "Not Applicable".
9	Enumeration	What is difference between consecutive numerical tick values on the y-axis?	* Your final answer should be the difference between consecutive numerical tick values of the y-axis, includ- ing the case when y-axis is shared across multiple sub- plots. When the y-axis is present on both the left and right of the plot, answer based on the axis at the left. Ignore units or scales that are written separately from the tick, such as units and scales from the axis label or the corner of the plot. * If the plot does not have an explicit y-axis tick value, or if the tick values are not numerical, or if the difference is not constant between all consecutive tick values, answer "Not Applicable".
10	Counting	How many lines are there?	 * Your final answer should be the number of lines in the plot. Ignore grid lines, tick marks, and any vertical or horizontal auxiliary lines. * If the plot does not contain any lines or is not considered a line plot, answer "Not Applicable".
11	Pattern Recognition	Do any lines intersect?	 * Your final answer should be "Yes" if any lines intersect, and "No" otherwise. Ignore grid lines, tick marks, and any vertical or horizontal auxiliary lines. * If the plot does not contain any lines or is not considered a line plot, answer "Not Applicable".
12	Counting	How many discrete labels are there in the legend?	 * Your final answer should account for only labels relevant to the plot in the legend, even if the legend is located outside the plot. * If the plot does not have a legend or no legend is not considered relevant to this plot, answer "Not Applicable".

continued ...

QID	Category	Question	Instructions
13	Enumeration	What are the names of the labels in the legend? (from top to bottom, then left to right)	 * You should write down the labels from top to bottom, then from left to right and separate the labels with commas. Your final answer should account for only labels relevant to the plot in the legend, even if the legend is located outside the plot. * If the plot does not have a legend or no legend is not considered relevant to this plot, answer "Not Applicable".
14	Enumeration	What is the difference between the maximum and minimum val- ues of the tick labels on the continuous legend (i.e., colorbar)?	 * You should remove the percentage sign (if any) in your answer. * If the plot does not have an explicit colorbar-based continuous legend or the legend is not considered relevant to this subplot, answer "Not Applicable".
15	Enumeration	What is the maximum value of the tick la- bels on the continuous legend (i.e., colorbar)?	 * You should remove the percentage sign (if any) in your answer. * If the plot does not have an explicit colorbar-based continuous legend or the legend is not considered relevant to this subplot, answer "Not Applicable".
16	Pattern Recognition	What is the general trend of data from left to right?	* Your final answer should be within a few words, such as "increases", "increases then stabilizes".
17	Composi- tionality	What is the total number of explicitly labeled ticks across all axes?	* Your final answer should be the total number of ex- plicitly labeled ticks across all axes, including the case when any axis is shared across multiple subplots.
18	Pattern Recognition	What is the layout of the subplots?	 * Your final answer should follow "n by m" format, where n is the number of rows and m is the number of columns. * If the plot does not contain subplots, answer "1 by 1".
19	Counting	What is the number of subplots?	 * Your final answer should be the total number of subplots in the plot. * If the plot does not contain subplots, answer "1".

O.2 Grading

In the grading process, we firstly group model responses and ground truths by their respective question number. Then, in each API call, we supply a number (5 by default) of response and ground-truth pairs to the GPT-4o judge to determine the correctness with the rubric and the in-context learning example. In the following examples, <|NUM_TRIPLETS|> will be replaced by the number of response and ground-truth pairs, <|JSON_KEYS|> will be replaced by the required json keys for GPT-4o's response (we use the json mode to better parse the extracted answers and scores). <|OVERARCHING_QUESTION|> will be replaced by the question as listed in Tab. 20. We designed several templates with different ICL examples due to the nature of the questions. Specifically:

- Question 1: Title (the answer should be related to the title)
- Question 2, 3, 4, 5, 6, 7: OCR (the answer can be a number of a short text, or not applicable)
- Question 8, 9, 10, 12, 14, 15, 17, 19: Quantitative (the answer should either be a number or not applicable)
- Question 11: Boolean (the answer should either be yes or no, with the possibility of not applicable)
- Question 13: Enum (the answer should be a long text connected by commas following a specific order)
- Question 16: Trend (the answer should be a generic descriptive phrase)
- Question 18: Layout (the answer should conform to "N by M")

```
You will be given <|NUM_TRIPLETS|> pairs of ground truth answers and
    model responses under an overarching question. You need to go
    through each of the pairs, extract the final answer from the
    model response, compare it with the ground truth answer, and then
    assign a binary score. Avoid providing explanations in your
    response. If there is no provided model response, please leave
    the extracted answer empty and give a score of 0. Your response
    must follow json formats with keys [<|JSON_KEYS|>] where the
    value for any 'extract_answer' is your extracted answer and '
    score' is an interger in [0, 1] based on the following rules:
Overarching Question: <|OVERARCHING_QUESTION|>
Rubric:
    * Give a score of 1 if and only if the extracted answer and the
       ground truth answer are referring to the same term. It's
       acceptable to have different grammar or form (e.g., \alpha and
       alpha; R<sup>2</sup>_{t,h,v,m} and R<sup>2</sup>_t,h,v,m). It's acceptable to omit
        letter prefixes (e.g., (a) Increment over time and Increment
       over time).
    * Give a score of 0 if any term in the extracted answer is
       different from the ground truth answer.
    * When ground truth answer is "Not Applicable", the response must
       express "Not Applicable" to receive a score of 1.
   ### Example Start ###
   T1:
   Response 1: The title of the plot is "The number of students in
       each grade".
   Ground Truth 1: The variance of students in each grade
   T2:
   Response 2: There is no title.
   Ground Truth 2: Not Applicable
   T3:
   Response 3: A_v^t
   Ground Truth 3: A<sup>t</sup>v
    ſ
       "extract_answer_T1": "The number of students in each grade",
       "score_T1": 0
       "extract_answer_T2: "Not Applicable",
       "score_T2": 1
       "extract_answer_T3": "A_v^t",
       "score_T3": 1
   }
    ### Example End ###
```

Grading Instruction for Q2, 3, 4, 5, 6, 7

```
You will be given <|NUM_TRIPLETS|> pairs of ground truth answers and
    model responses under an overarching question. You need to go
    through each of the pairs, extract the final answer from the
    model response, compare it with the ground truth answer, and then
    assign a binary score. Avoid providing explanations in your
    response. If there is no provided model response, please leave
    the extracted answer empty and give a score of 0. Your response
    must follow json formats with keys [<|JSON_KEYS|>] where the
    value for any 'extract_answer' is your extracted answer and '
    score' is an interger in [0, 1] based on the following rules:
Overarching Question: <|OVERARCHING_QUESTION|>
Rubric:
    * Give a score of 1 if and only if the extracted answer and the
       ground truth answer are referring to the same term. It's
       acceptable to have equivalent grammar or form (e.g., \alpha and
       alpha; R<sup>2</sup>_{t,h,v,m} and R<sup>2</sup>_t,h,v,m). If the ground truth is
       a number, the extracted answer should be the number with the
       exact same value.
    * Give a score of 0 if any term in the extracted answer is
       different from the ground truth answer, or if the extracted
       number is different in value from the ground truth number.
    * When ground truth answer is "Not Applicable", the response must
       express "Not Applicable" to receive a score of 1.
   ### Example Start ###
   T1:
   Response 1: The answer is 1.0
   Ground Truth 1: 1.00
   Т2:
   Response 2: By manually inspecting the plot, the final answer
       should be 0.
   Ground Truth 2: Not Applicable
   T3:
   Response 3: A_v^t
   Ground Truth 3: A<sup>t</sup>v
    {
       "extract_answer_T1": 1.0,
       "score_T1": 1
       "extract_answer_T2: 0,
       "score_T2": 0
       "extract_answer_T3": "A_v^t",
       "score_T3": 1
   }
   ### Example End ###
```

Grading Instruction for Q8, 9, 10, 12, 14, 15, 17, 19

```
You will be given <|NUM_TRIPLETS|> pairs of ground truth answers and
   model responses under an overarching question. You need to go
   through each of the pairs, extract the final answer from the
   model response, compare it with the ground truth answer, and then
    assign a binary score. Avoid providing explanations in your
   response. If there is no provided model response, please leave
   the extracted answer empty and give a score of 0. Your response
   must follow json formats with keys [<|JSON_KEYS|>] where the
   value for any 'extract_answer' is your extracted answer and '
   score' is an interger in [0, 1] based on the following rules:
Overarching Question: <|OVERARCHING_QUESTION|>
Rubric:
   * Give a score of 1 if and only if the extracted answer and the
       ground truth answer are numbers with the exact same value.
   * Give a score of 0 if the extracted answer is different in value
       from the ground truth answer.
   * When ground truth answer is "Not Applicable", the response must
       express "Not Applicable" to receive a score of 1.
   ### Example Start ###
   T1:
   Response 1: 5
   Ground Truth 1: 6
   Т2.
   Response 2: 0
   Ground Truth 2: Not Applicable
   T3:
   Response 3: 4
   Ground Truth 3: 4
   {
       "extract_answer_T1": 5,
       "score_T1": 0
       "extract_answer_T2: 0,
       "score_T2": 0
       "extract_answer_T3": 4,
       "score_T3": 1
   }
   ### Example End ###
```

```
You will be given <|NUM_TRIPLETS|> pairs of ground truth answers and
   model responses under an overarching question. You need to go
   through each of the pairs, extract the final answer from the
   model response, compare it with the ground truth answer, and then
    assign a binary score. Avoid providing explanations in your
   response. If there is no provided model response, please leave
   the extracted answer empty and give a score of 0. Your response
   must follow json formats with keys [<|JSON_KEYS|>] where the
   value for any 'extract_answer' is your extracted answer and '
   score' is an interger in [0, 1] based on the following rules:
Overarching Question: <|OVERARCHING_QUESTION|>
Rubric:
   * Give a score of 1 if and only if the extracted answer and the
       ground truth answer are the same.
   * Give a score of 0 if the extracted answer and the ground truth
       answer are different.
   * When ground truth answer is "Not Applicable", the response must
       express "Not Applicable" to receive a score of 1.
   ### Example Start ###
   T1:
   Response 1: No, there are no intersections.
   Ground Truth 1: no
   Т2.
   Response 2: No, all the lines are parallel.
   Ground Truth 2: Yes
   T3:
   Response 3: There are no lines in the plot.
   Ground Truth 3: Not Applicable
   {
       "extract_answer_T1": "No",
       "score_T1": 1
       "extract_answer_T2: "No",
       "score_T2": 0
       "extract_answer_T3": "Not Applicable",
       "score_T3": 1
   }
   ### Example End ###
```

```
You will be given <|NUM_TRIPLETS|> pairs of ground truth answers and
   model responses under an overarching question. You need to go
   through each of the pairs, extract the final answer from the
   model response, compare it with the ground truth answer, and then
    assign a binary score. Avoid providing explanations in your
   response. If there is no provided model response, please leave
   the extracted answer empty and give a score of 0. Your response
   must follow json formats with keys [<|JSON_KEYS|>] where the
   value for any 'extract_answer' is your extracted answer and '
   score' is an interger in [0, 1] based on the following rules:
Overarching Question: <|OVERARCHING_QUESTION|>
Rubric:
   * Give a score of 1 if and only if the extracted answer and the
       ground truth answer are referring to the same term. It's
       acceptable to have equivalent grammar or form (e.g., \alpha and
       alpha; R^2_{t,h,v,m} and R^2_{t,h,v,m}. The order of the terms
       must be the same.
   * Give a score of 0 if any term in the extracted answer is
       different from the ground truth answer, or if the order of the
        terms is different.
   * When ground truth answer is "Not Applicable", the response must
       express "Not Applicable" to receive a score of 1.
   ### Example Start ###
   T1:
   Response 1: Here are the names of the labels: A, B, C
   Ground Truth 1: B, A, C
   T2:
   Response 2: The labels are T56, B33.
   Ground Truth 2: T56,B33,A12
   T3:
   Response 3: \alpha, \beta, \gamma^t_v
   Ground Truth 3: \alpha, \beta, \gamma_v<sup>t</sup>
   {
       "extract_answer_T1": "A, B, C",
       "score_T1": 0
       "extract_answer_T2: "T56, B33",
       "score_T2": 0
       "extract_answer_T3": "\alpha, \beta, \gamma^t_v",
       "score_T3": 1
   }
   ### Example End ###
```

```
You will be given <|NUM_TRIPLETS|> pairs of ground truth answers and
   model responses under an overarching question. You need to go
   through each of the pairs, extract the final answer from the
   model response, compare it with the ground truth answer, and then
    assign a binary score. Avoid providing explanations in your
   response. If there is no provided model response, please leave
   the extracted answer empty and give a score of 0. Your response
   must follow json formats with keys [<|JSON_KEYS|>] where the
   value for any 'extract_answer' is your extracted answer and '
   score' is an interger in [0, 1] based on the following rules:
Overarching Question: <|OVERARCHING_QUESTION|>
Rubric:
   * Give a score of 1 if and only if the extracted answer and the
       ground truth answer share the same general trend.
   * Give a score of 0 if the extracted answer and the ground truth
       answer are different in trend expression.
   ### Example Start ###
   T1:
   Response 1: there is an increase in the data from left to right
   Ground Truth 1: Decreases
   Т2.
   Response 2: the curves move up and stay constant
   Ground Truth 2: Increases then stabilizes
   ТЗ·
   Response 3: Decreases
   Ground Truth 3: Decreases then increases
   ſ
       "extract_answer_T1": "Increases",
       "score_T1": 0
       "extract_answer_T2: "Move up and stay constant",
       "score_T2": 1
       "extract_answer_T3": "Decreases",
       "score_T3": 0
   }
   ### Example End ###
```

```
You will be given <|NUM_TRIPLETS|> pairs of ground truth answers and
   model responses under an overarching question. You need to go
   through each of the pairs, extract the final answer from the
   model response, compare it with the ground truth answer, and then
    assign a binary score. Avoid providing explanations in your
   response. If there is no provided model response, please leave
   the extracted answer empty and give a score of 0. Your response
   must follow json formats with keys [<|JSON_KEYS|>] where the
   value for any 'extract_answer' is your extracted answer and '
   score' is an interger in [0, 1] based on the following rules:
Overarching Question: <|OVERARCHING_QUESTION|>
Rubric:
   * Give a score of 1 if and only if the extracted answer and the
       ground truth answer are the same in terms of the number of
       rows and columns (e.g., n by m).
   * Give a score of 0 if the extracted answer is different from the
       ground truth answer.
   ### Example Start ###
   T1:
   Response 1: 2 by 3
   Ground Truth 1: 3 by 2
   T2:
   Response 2: the layout is 1 by 1
   Ground Truth 2: 1 by 1
   T3:
   Response 3: there are two rows and three columns
   Ground Truth 3: 2 by 3
   {
       "extract_answer_T1": "2 by 3",
       "score_T1": 0
       "extract_answer_T2: "1 by 1",
       "score_T2": 1
       "extract_answer_T3": "2 by 3",
       "score_T3": 1
   }
   ### Example End ###
```

P Prompts for Reasoning Questions

P.1 Response Generation

In response generation for reasoning questions, we replace {Question} with the actual question and apply the instruction based on its respective question type. For number-in-general questions, only one of the two bullet points will be used depending on the format of the answer. In particular, if the answer has a specific decimal place, we replace {num_decimal} to the actual number of decimal places. This follows the design of MathVista [60].

{Question} * Your final answer must be grounded to some text that is explicitly written and relevant to the question in the chart. * If you need to answer multiple terms, separate them with commas. * Unless specified in the question (such as answering with a letter), you are required to answer the full names of subplots and/or labels by default.

{Question}

- * If there are options in the question, your final answer must conform to one of the options.
- * If there are additional instructions in the question, follow them accordingly.
- * If there are neither options nor additional instructions, you are allowed to respond with a short phrase only.

Insturctions for Number-in-Chart Questions

{Question}

- * Your final answer must be grounded to a number that is exlicitly written and relevant to the question in the chart, even if it 's an approximate value.
- \ast You are allowed to extract numbers within some text when needed.

Insturctions for Number-in-General Questions

```
{Question}
* Your final answer must be an exact integer.
(OR)
* Your final answer must be a number with {num_decimal} decimal
    places.
```

P.2 Grading

In the grading process, we make an API call for each triplet of (question, ground truth, response). For each type of questions, we provide two in-context learning examples before supplying the triplet. In formatting the template, we replace <|question|>, <|ground_truth|>, <|response|> with their respective values. Note that for the question, we only supply the original question without answer-type-based instructions that are used to generate the model response.

```
Grading Instructions for Text-in-Chart Questions
You will be given a question, a ground truth answer and a model
    response. You need to extract the final answer from the model
    response, compare it with the ground truth answer, and then
    assign a binary score. Avoid providing explanations in your
    response. If there is no provided model response, please leave
    the extracted answer empty and give a score of 0.
Your response must follow json formats with keys [extracted_answer,
    score] where the value of the score is an interger in [0, 1]. You
    must follow the scoring rules:
### Rules ###
* Give a score of 1 if and only if the final answer and the ground
    truth answer are referring to the same term. It's acceptable to
    have different grammar or form (e.g., \alpha and alpha; R<sup>2</sup>_{t,h,v,m}
    and R<sup>2</sup>_t,h,v,m). It's also acceptable to have different orders
    of the terms when question asks for multiple terms.
* Give a score of 0 if any term (e.g., ACC+ and ACC; P-101 and P=101)
     is different between the final answer and the ground truth.
### Example 1 Starts ###
* Question: What is the name of the curve that intersects y=\lambda
    exactly three times?
* Ground Truth: P56962
* Response: There is only one curve that intersects y=\lambda exactly
     three times. The name of the curve is written as P55762.
{
    "extracted_answer": "P55762",
   "score": 0
}
### Example 1 Ends ###
### Example 2 Starts ###
* Question: What is the letter of the subplot where all bars are
    above 35?
* Ground Truth: (b)
* Response: The letter of the subplot where all bars are above 35 is
    b.
{
    "extracted_answer": "b",
   "score": 1
}
### Example 2 Ends ###
### Your Turn ###
* Question: <|question|>
* Ground Truth: <|ground_truth|>
* Response: <|response|>
```

```
Grading Instructions for Text-in-General Questions
You will be given a question, a ground truth answer and a model
   response. You need to extract the final answer from the model
   response, compare it with the ground truth answer, and then
   assign a binary score. Avoid providing explanations in your
   response. If there is no provided model response, please leave
   the extracted answer empty and give a score of 0.
Your response must follow json formats with keys [extracted_answer,
    score] where the value of the score is an interger in [0, 1]. You
    must follow the scoring rules:
### Rules ###
* If there are predefined options in the question:
   * Give a score of 1 if the final answer matches the ground truth
       answer exactly.
   * Give a score of 0 if the final answer does not match the ground
       truth answer.
* If there are no predefined options in the question:
   * Give a score of 1 if the final answer shares the same semantic
       meaning with the ground truth answer (e.g., "increasing then
       decreasing" and "moving up then down"; "converge" and "move
       closer together").
   * Give a score of 0 if the final answer shares different semantic
       meanings from the ground truth answer (e.g., "increasing then
       decreasing" and "remain constant"; "converge" and "diverge").
### Example 1 Starts ###
* Question: What is the trend of the red curve between t=10 and t=25?
* Ground Truth: increasing then decreasing
* Response: The red curve is increasing between t=10 and t=25.
{
   "extracted_answer": "increasing",
   "score": 0
}
### Example 1 Ends ###
### Example 2 Starts ###
* Question: What is the interval where the blue curve achieves the
   maximum value among [0, 50], [50, 100], [100, 150], and [150,
   200]?
* Ground Truth: [50, 100]
* Response: The interval where the blue curve achieves the maximum
   value is [50, 100].
{
   "extracted_answer": "[50, 100]",
   "score": 1
7
### Example 2 Ends ###
### Your Turn ###
* Question: <|question|>
* Ground Truth: <|ground_truth|>
* Response: <|response|>
```

```
Grading Instructions for Number-in-Chart Questions
You will be given a question, a ground truth answer and a model
   response. You need to extract the final answer from the model
   response, compare it with the ground truth answer, and then
   assign a binary score. Avoid providing explanations in your
   response. If there is no provided model response, please leave
   the extracted answer empty and give a score of 0.
Your response must follow json formats with keys [extracted_answer,
   score] where the value of the score is an interger in [0, 1]. You
    must follow the scoring rules:
### Rules ###
* Give a score of 1 if and only if the two numbers are exactly equal
   in values. It's acceptable to have different notations (e.g., 0.01
     and 10<sup>-2</sup>; 1500 and 1.5e3).
* Give a score of 0 if the two numbers are different in values.
### Example 1 Starts ###
* Question: What is the value of the red curve at t=10?
* Ground Truth: 0.01
* Response: The value of the red curve at t=10 is 0.012.
{
   "extracted_answer": "0.012",
   "score": 0
}
### Example 1 Ends ###
### Example 2 Starts ###
* Question: What is the value of the blue curve at t=50?
* Ground Truth: 1500
* Response: The value of the blue curve at t=50 is 1.5e3.
{
   "extracted_answer": "1.5e3",
   "score": 1
}
### Example 2 Ends ###
### Your Turn ###
* Question: <|question|>
* Ground Truth: <|ground_truth|>
* Response: <|response|>
```

```
Grading Instructions for Number-in-General Questions
You will be given a question, a ground truth answer and a model
   response. You need to extract the final answer from the model
   response, compare it with the ground truth answer, and then
   assign a binary score. Avoid providing explanations in your
   response. If there is no provided model response, please leave
   the extracted answer empty and give a score of 0.
Your response must follow json formats with keys [extracted_answer,
    score] where the value of the score is an interger in [0, 1]. You
    must follow the scoring rules:
### Rules ###
* Give a score of 1 if and only if the two numbers are exactly equal
   in values. It's acceptable to have different notations (e.g., 0.01
     and 10<sup>-2</sup>; 1500 and 1.5e3).
* Give a score of 0 if the two numbers are different in values.
### Example 1 Starts ###
* Question: What is the value of the red curve at t=10?
* Ground Truth: 0.01
* Response: The value of the red curve at t=10 is 0.012.
{
   "extracted_answer": "0.012",
   "score": 0
}
### Example 1 Ends ###
### Example 2 Starts ###
* Question: What is the value of the blue curve at t=50?
* Ground Truth: 1500
* Response: The value of the blue curve at t=50 is 1.5e3.
{
   "extracted_answer": "1.5e3",
   "score": 1
}
### Example 2 Ends ###
### Your Turn ###
* Question: <|question|>
* Ground Truth: <|ground_truth|>
* Response: <|response|>
```

Q Chart-Free Random Baseline Prompts

We provide the prompts we use for our chart-free random baseline:

* Randomly guess a reasonable answer based on the question only. If the question asks for a number, you can randomly guess a number within a reasonable range. If the question asks for a term, you can randomly guess a term that is relevant to the question.

R Data Annotation Platform

We use LabelStudio [79] as the platform for all our data annotations. We host LabelStudio in our internal clusters so that annotators can connect to the server conveniently via SSH-forwarding.

R.1 Chart Selection



Figure 9: Screenshot of our chart selection process. As shown in the screenshot, annotators are required to select one chart from 10 candidates figures that are pre-filtered with a cosine similarity > 0.65 compared to the average chart embedding from MathVista.

R.2 Descriptive Question Annotation

📕 Label Studio 📃 Projects / charx	iv - descriptive questions / Labeli	ing	Settings	
#8474 < >				
Difference in the gain at zenth	 Q6: What is the lowest tick on the20 Q14: What is the labeled range (r continuous legend? -0 Q5: What is the right-most tick or -250 Q15: What is the maximum label continuous legend? -0 Q9: What is the difference betwee numerical tick labels on the y-axis -5 Q4: What is the left-most tick on -50 Q3: What is the label of the y-axis -0ifference (%) Q10: How many lines are there in -6 Q18: What is the layout of the su your answer as m by n, where m, number of rows and columns rest -1 by 1 	e y-axis? max-min) of the n the x-axis? ed value on the en consecutive is? the x-axis? s? the plot? bplots? Give n are the spectively.	Q8: What is difference between consecutive numerical tick labels on the x-axis? - 25 Q11: If the plot contains line-charts, do any lines intersect? - Yes Q1: What is the title for the chart? - Difference in the gain at zenith Q13: What is the title for the chart? - Difference in the gain at zenith Q13: What are the discrete labels shown in the legend. Answer from top to bottom then left to right. - Model a, Model c without flanges, Model c with flanges, Model d, Model e, Model f Q2: What is the label of the x-axis? - Frequency (MHZ) Q12: How many discrete labels are there in the legend? - 6 Q7: What is the general trend of data from left to right? Answer within a few words, such as 'increases', 'increases then stabilizes' - Fluctuating Q17: What is the total number of explicitly labeled ticks across the axes? - 18	
Number of subplots (e.g., 3)		qid1 (e.g.,	aid1 (e.g., 50, 10)	
1 0		6	-20	
Fill in one of them		qid2 (e.g., 4)	aid2 (e.g., -1)	
Row, column to ask Q with (e.g., 2,3)		5	250	
identifier if not grid (e.g., the subplot titled)		qid3 (e.g., 2)	aid3 (e.g., Length)	
		9 📋 uqid1 (e.g.,	5	4
		14		

Figure 10: Screenshot of our descriptive task annotation process. As shown in the screenshot, the annotator is presented with a chart and a randomly shuffled list of the 18 descriptive tasks (except Q19, which asks for the number of subplots and can be automatically converted from the number of subplot metadata) with GPT-generated answers. The annotator is required to select the first 3 answerable questions and the first unanswerable question with ground truth answers, fill in the number of subplots and the row, column number of the subplots to ask questions with (if the chart contains subplots).

R.3 Reasoning Question Annotation

📘 Label Studio	Projects /	harxiv - reasoning question construction / Labeling	Settings
5506 < >			
Please enter the fir	$\frac{7}{12} = 3$	Image: Second	<pre>>m \(\tau = 8\) curve on the plot? rror? nore stable error value after iteration ow a mean square error of \ it \(\tau = 8\)' at iteration 100 in iddel? D0? e highest variability in mean square e error?</pre>
How many curves maint Please enter the fin	ain a mean square error bel nal answer (press e	w 10 [~] -2 after 120k iterations?	
How can someone Respond using text th Respond using a spec Respond using a spec Respond using text, w How is this question The question was sou The question was add Neither the question r	e respond to the que that is already provided in the lift number that is listed in ciftic number, which may or n which may or may not be in t on formulated? urced from one of the candit apted from one of the candit nor the answer was derived	stion unambiguously? chart. ^[1] the chart. ^[2] ay not be in the chart. ^[3] te chart. ^[4] ates, and answer was sourced or modified. ^[4] ates, and the answer was also modified. ^[4] rom the candidates. ^[6]	

Figure 11: Screenshot of our reasoning task annotation process. As shown in the screenshot, the annotator is presented with a chart and a list of reasoning QAs automatically generated by GPT-4V. Then, the annotator needs to decide the final question to fill in (*i.e.*, GPT-sourced, GPT-inspired, or human-written), and write down the final answer with an answer type (*i.e.*, Text-in-Chart, Text-in-General, Number-in-Chart, Number-in-General). The answer type is subsequently used in the response generation process to provide additional instructions in generating response for the question.

S Examples from Modified-Question Set

S.1 Example 1





S.2 Example 2



Question: What is the approximate difference between the y-values of the firebrick and orange points when the x-axis value is 0? **Answer**: 4

S.3 Example 3



Question: What's the computing and wirless total for semiconductor demand in 2014? **Answer**: 197.3



S.4 Example 4





S.5 Example 5





T Examples from Modified-Chart Set

T.1 Example 1





T.2 Example 2





T.3 Example 3





T.4 Example 4

	Original Chart (Source: FigureQA)
title	
Navy Blue -	
Teal -	
Rosy Brown -	
g Sienna -	
Iight Salmon -	
Rebecca Purple -	
Olive Drab -	
Lime Green -	
0 20 40 60 80 10 xayis label	
Question: Is Rebecca Purn	le greater than Alive Drah?
A normany Na	le greater than Onve Diad?
Answer: No	
	Modified Chart
SAR-4 (107)200 SAR-5 (102)200 EBP-2d (102)200 Treword (102) VisitAll (1020) VisitAll (1020) 0 5 10 15 20	
Question : Is ExBw-2d greater	ater than Tireworld?
Answer: No	

T.5 Example 5



Question: How many items sold less than 1 units in at least one store? **Answer**: 0



U Common Failure Cases of Descriptive Questions

We provide 30 concrete examples on each of the descriptive questions in which the vast majority of representative models fail to provide the correct answer. Common failures of models include:

- Models cannot correctly **localize** subplot when **many subplots are present** (Apps. U.1, U.10, U.11, U.18 and U.26).
- Models use **incorrect elements** of the charts to provide an answer (Apps. U.2, U.4, U.5, U.6, U.7, U.8, U.9, U.10, U.12, U.15, U.22 and U.25).
- Models make OCR mistakes (Apps. U.2, U.3, U.5, U.9, U.15 and U.19).
- Models fail to identify relevant elements when they are **not** close to the subplot (Apps. U.3 and U.23).
- Models hallucinate (Apps. U.13, U.16, U.17, U.20, U.24 and U.26).
- Models fail to tackle tricky or unconventional scenarios (Apps. U.14, U.21 and U.27).
- Models fail to count (Apps. U.15, U.28, U.29 and U.30).

Table 21: Overview of failure case examples in descriptive questions. We provide 30 examples for each of the descriptive questions with both answerable and unanswerable scenarios.

Example	QID	Answerable
1 2	1	√ ×
3 4	2	√ ×
5 6	3	√ ×
7	4	\checkmark
8	5	\checkmark
9	6	\checkmark
10	7	✓
11 12	8	√ ×
13 14	9	√ ×
15 16	10	√ ×
17 18	11	✓ ×
19 20	12	✓ ×
21 22	13	✓ ×
23 24	14	✓ ×
25 26	15	✓ ×
27	16	\checkmark
28	17	\checkmark
29	18	\checkmark
30	19	1

U.1 Example 1



U.2 Example 2



IDEFICS 2: Powell Q&A.

U.3 Example 3



IDEFICS 2: **BJD-245000**.

U.4 Example 4



MGM HD Yi 34B: The label of the x-axis in the subplot at row 2 and column 1 is "Stock". This label is explicitly written at the bottom of the plot, indicating the time series data points are measured against the stock variable.

IDEFICS 2: Stock.

U.5 Example 5



IDEFICS 2: Load & QoS.

U.6 Example 6

Example
$ \begin{matrix} b_1 & b_2 & b_3 & b_1 & b_2 & b_2 & b_1 & b$
<pre>Question: For the subplot at row 1 and column 3, what is the label of the y-axis? * Your final answer should be the label of the y-axis that is explicitly written, including the case when y-axis is shared across multiple subplots. When the y-axis is present on both the left and right of the plot, answer the label of the y-axis at the left. * If the plot does not have an explicit y-axis label, answer 'Not Applicable'. Answer: Not Applicable</pre>

GPT-40: The label of the y-axis for the subplot at row 1 and column 3 is 'Not Applicable'.

Claude 3 Sonnet: The y-axis label for the subplot in row 1, column 3 is "% Win Rate".

Reka Core: The label of the y-axis for the subplot at row 1 and column 3 is 'Total'. This is explicitly written on the y-axis of the bar chart. The y-axis is shared across multiple subplots, but the label 'Total' is present on the left side of this particular subplot.

InternVL Chat V1.5: The label of the y-axis for the subplot at row 1 and column 3 is "% Win Rate (c)".

MGM HD Yi 34B: The label of the y-axis for the subplot at row 1 and column 3 is 'Win Rate'. This label is explicitly written and is shared across all three subplots in the first row.

IDEFICS 2: Recognition.

U.7 Example 7



MGM HD Yi 34B: The leftmost labeled tick on the x-axis of the bottom right subplot is "-50". This is determined by looking at the numerical values written on the x-axis, which are aligned with the corresponding bars. The "-50" tick is the first one on the left side of the x-axis, indicating the lowest value on the scale presented in this subplot.

IDEFICS 2: BIC.

U.8 Example 8



GPT-40: The rightmost labeled tick on the x-axis for the subplot at row 1 and column 5 is "Setref Concept".

Claude 3 Sonnet: The rightmost labeled tick on the x-axis for the subplot in row 1, column 5 is Setref(Concept).

Reka Core: The rightmost labeled tick on the x-axis for the subplot at row 1 and column 5 is 0.15. This is the value explicitly written on the x-axis, which represents the p-value for the Edit metric in the ShapeWorld dataset. The p-value is a statistical measure that helps determine the significance of the results, with lower values typically indicating a more statistically significant difference.

InternVL Chat V1.5: The rightmost labeled tick on the x-axis for the subplot at row 1 and column 5 is 0.05.

MGM HD Yi 34B: The rightmost labeled tick on the x-axis of the subplot at row 1 and column 5 is "0.0". This is determined by looking at the bottom axis of the plot, where the x-axis is shared across all subplots. The tick values are written directly on the axis, and the rightmost one is clearly marked as "0.0".

IDEFICS 2: Ref Concept.

U.9 Example 9



Reka Core: The spatially lowest labeled tick on the y-axis of the current plot is "Alex daily 4.00PM". This is determined by visually scanning the y-axis from top to bottom and identifying the lowest label that is clearly written and associated with the y-axis. The label "Alex daily 4.00PM" is at the bottom of the y-axis, indicating it is the lowest labeled tick.

InternVL Chat V1.5: -1.00

MGM HD Yi 34B: The spatially lowest labeled tick on the y-axis is -0.50. This is determined by looking at the y-axis on the left side of the plot, where the ticks are clearly marked. The lowest tick is the first one on the left, which is labeled with the value-0.50.

IDEFICS 2: CC daily 4**.**00PM.

U.10 Example 10



Claude 3 Sonnet: The spatially highest labeled tick value on the y-axis for the subplot at row 2 and column 1 is 4.

Reka Core: The spatially highest labeled tick on the y-axis for the subplot at row 2 and column 1 is 5. This is determined by looking at the y-axis on the left side of the subplot, where the ticks are labeled. The tick values increase from the bottom to the top of the subplot, and the highest labeled tick is clearly marked as 5.

InternVL Chat V1.5: The spatially highest labeled tick on the y-axis for the subplot at row 2 and column 1 is 100.

MGM HD Yi 34B: The spatially highest labeled tick on the y-axis of the subplot at row 2 and column 1 is 2.85 m. This is determined by looking at the y-axis on the left side of the plot, where the highest labeled tick is clearly marked.

IDEFICS 2: 1.0.

U.11 Example 11


U.12 Example 12



GPT-40: The difference between consecutive numerical tick values on the x-axis for the subplot at row 1 and column 1 is 20.

Claude 3 Sonnet: The difference between consecutive numerical tick values on the x-axis for the subplot at row 1 and column 1 is **Not Applicable**. The x-axis shows text labels ("110 items" and "agreement, 12 items") rather than numerical tick values.

Reka Core: The x-axis of the subplot at row 1 and column 1 is labeled with numerical values ranging from 0 to 100. The tick marks are evenly spaced, and the difference between consecutive numerical tick values is consistent. To determine this difference, we can look at any two consecutive ticks and calculate the interval between them. For example, between the tick at 0 and the tick at 20, the difference is 20. Similarly, between the tick at 20 and the tick at 40, the difference is also 20. This pattern continues across the x-axis, indicating that the difference between consecutive numerical tick values is 20.

InternVL Chat V1.5: 10

MGM HD Yi 34B: The subplot at row 1 and column 1 has an x-axis with numerical tick values. The difference between consecutive numerical tick values on the x-axis is 10. This is determined by observing the numerical labels on the x-axis, which are evenly spaced and increase by 10 units between each label.

IDEFICS 2: 1.

U.13 Example 13



Claude 3 Sonnet: The difference between consecutive numerical tick values on the y-axis for the subplot at row 2 and column 1 is 2.5.

Reka Core: The y-axis tick values on the subplot at row 2 and column 1 are numerical and evenly spaced. The values are -5, -4, -3, -2, -1, 0, 1, 2, 3, 4, 5. The difference between consecutive numerical tick values is 1.

InternVL Chat V1.5: The difference between consecutive numerical tick values on the y-axis for the subplot at row 2 and column 1 is 0.2.

MGM HD Yi 34B: The subplot at row 2 and column 1 shows a numerical y-axis with tick values. The difference between consecutive numerical tick values on the y-axis is 1. This is determined by observing the numerical values on the y-axis, which are -5, -4, -3, -2, -1, 0, 1, 2, 3, 4, 5, and so on. The difference between any two consecutive values is 1.

IDEFICS 2: 0.1.

U.14 Example 14

Example
 a) (1) (1) (1) (1) (1) (1) (1) (1) (1) (1
GPT-40 : The difference between consecutive numerical tick values on the y-axis for the subplot at row 1 and column 1 is 0.08.
Claude 3 Sonnet : The difference between consecutive numerical tick values on the y-axis for the subplot in row 1, column 1 is 0.09.
Reka Core : The y-axis of the subplot at row 1 and column 1 has numerical tick values at 0.04, 0.08, 0.12, and 0.16. The difference between consecutive numerical tick values is 0.04.

InternVL Chat V1.5: The difference between consecutive numerical tick values on the y-axis of subplot at row 1 and column 1 is 0.01.

MGM HD Yi 34B: The difference between consecutive numerical tick values on the y-axis of the subplot at row 1 and column 1 is 0.08. This is determined by observing the numerical values on the y-axis and noting the difference between the first two visible values, which are 0.08 and 0.17. Since the values are numerical and the difference is constant between all consecutive tick values, the answer is not "Not Applicable".

IDEFICS 2: 0.05.





GPT-40: The subplot at row 1 and column 2 contains 5 lines.

Claude 3 Sonnet: For the subplot in the second column, there are 5 lines plotted, corresponding to different values of J/U = 0.18, 0.12, 0.06, 0.0, and the reference line labeled "Ref. [14]".

Reka Core: There are 5 lines in the subplot at row 1 and column 2. These lines correspond to the different J/U ratios as indicated by the legend: J/U=0.18, J/U=0.12, J/U=0.06, J/U=0.14, and the reference line from Ref. [14]. Each line is represented by a different color and symbol combination, and they all follow the same path across the plot, showing the variation of the quantity $\overline{V}^{(2)}(q)$ with respect to the momentum transfer q along the high-symmetry points in the Brillouin zone.

InternVL Chat V1.5: There are five lines in the plot.

MGM HD Yi 34B: The subplot at row 1 and column 2 contains four lines. These lines represent different values of the J/U ratio, as indicated by the legend in the top left corner of the image. The lines are differentiated by color and are plotted against the variable q.

IDEFICS 2: 4.

U.16 Example 16



GPT-40: Not Applicable

Claude 3 Sonnet: The plot contains 4 lines, each representing a different range of percentages: 0%-5%, 5%-10%, 10%-20%, and >20%.

Reka Core: The plot in the image is a bar chart, not a line plot. Therefore, it does not contain any lines in the traditional sense of a line plot. The bars are composed of stacked segments, but these are not lines. Hence, the answer is "**Not Applicable**".

InternVL Chat V1.5: 4

MGM HD Yi 34B: The plot contains a total of four lines, each representing a different percentage range of the data. These lines are used to differentiate the data points by their respective percentage categories.

IDEFICS 2: 10.

U.17 Example 17



GPT-40: Yes.

Claude 3 Sonnet: To determine if any lines intersect in the subplot at row 1, column 5, I will carefully examine the plot lines, ignoring grid lines, tick marks, and auxiliary lines. In this subplot, there appears to be a single line plotted in red. The line has some fluctuations but does not intersect or cross itself at any point.

Since there is only one line present and it does not intersect itself, my answer is: No

Reka Core: No.

InternVL Chat V1.5: No, the lines in the subplot at row 1 and column 5 do not intersect.

MGM HD Yi 34B: In the subplot at row 1 and column 5, the lines do not intersect. The blue line is a solid line that remains above the zero line, while the orange line is a dashed line that remains below the zero line throughout the plot. There is no point where the two lines cross each other. Therefore, the answer to the question is "No".

IDEFICS 2: No.

U.18 Example 18



GPT-40: No.

Claude 3 Sonnet: Yes, the two lines in the bottom left subplot intersect at a point around (0.5, 0) based on the scatter plot and fitted lines shown.

Reka Core: No.

InternVL Chat V1.5: No

MGM HD Yi 34B: The bottom left subplot does not contain any lines; it is a histogram. Therefore, the question of whether lines intersect is **not applicable** to this subplot.

IDEFICS 2: No.

U.19 Example 19



IDEFICS 2: 5.

U.20 Example 20



IDEFICS 2: 2.

the question is three.

U.21 Example 21

Example
i 1 0
Question: For the current plot, what are the names of the labels in the legend? * You should write down the labels from top to bottom, then from left to right and separate the labels with commas. Your final answer should account for only labels relevant to the plot in the legend, even if the legend is located outside the plot. * If the plot does not have a legend or no legend is not considered relevant to this plot, answer "Not Applicable". Answer: min, max, max+1, max+max, 2, 5, 20
GPT-40 : min, max, max+1, max+max, Unknown Vals , 2, 5, 20
Claude 3 Sonnet : The labels in the legend from top to bottom, then left to right are: Setting, min, max, max+1, max+max, Unknown Vals, 2, 5, 20.
Reka Core : The labels in the legend, from top to bottom, then from left to right, are: "Setting", "min", "max", "max+1", "max+max", "Unknown Vals", "2", "5", "20". Therefore, the final answer is: Setting, min, max, max+1, max+max, Unknown Vals, 2, 5, 20.
InternVL Chat V1.5: Setting, min, max, max+1, max+max, Unknown Vals, 2, 5, 20

MGM HD Yi 34B: The labels in the legend, from top to bottom and from left to right, are as follows: "min", "max", "max+1", "max+max", "Unknown Vals", "2", "5", and "20".

IDEFICS 2: Not Applicable.

U.22 Example 22



MGM HD Yi 34B: The labels in the legend of the subplot at row 1 and column 1 are "Intensity (arb. units)". These labels are relevant to the plot as they correspond to the color scale used to represent the intensity of the energy loss in the scatter plot.

IDEFICS 2: Incident energy (eV), Intensity (arb. units).

U.23 Example 23



GPT-40: The subplot at row 5 and column 2 does not have an explicit colorbar-based continuous legend. Therefore, the answer is "Not Applicable".

Claude 3 Sonnet: Not Applicable

Reka Core: The continuous legend in the subplot at row 5 and column 2, labeled C2S, ranges from 0 to 200. The maximum value is 200 and the minimum value is 0. Therefore, the difference between the maximum and minimum values of the tick labels on the continuous legend is 200.

InternVL Chat V1.5: The subplot at row 5 and column 2 has a continuous legend (colorbar) on the right side of the plot. The tick labels on the colorbar range from 0 to 200. The difference between the maximum and minimum values of the tick labels is 200 - 0 = 200.

MGM HD Yi 34B: The subplot at row 5 and column 2 does not have an explicit colorbar-based continuous legend. Instead, it has a scatter plot with a color-coded legend on the right side, which is not relevant to the question about the difference between the maximum and minimum values of the tick labels on the continuous legend. Therefore, the answer is "Not Applicable".

IDEFICS 2: Not Applicable.

U.24 Example 24



MGM HD Yi 34B: The bottom right subplot of the "Generalised Fisher" section shows a continuous legend with tick labels ranging from 0.8 to 2.3. The maximum value is 2.3, and the minimum value is 0.8. Therefore, the difference between the maximum and minimum values of the tick labels on the continuous legend is 1.5.

IDEFICS 2: 0.1.

U.25 Example 25



GPT-40: The subplot at row 2 and column 1 is labeled "c" and is titled "Probability of static coverage." The maximum value of the tick labels on the continuous legend (colorbar) for this subplot is 1.0.

Claude 3 Sonnet: Not Applicable

Reka Core: 35.

InternVL Chat V1.5: 35

MGM HD Yi 34B: The maximum value of the tick labels on the continuous legend (colorbar) for the subplot at row 2 and column 1 is 10^1 . This is determined by observing the colorbar on the right side of the subplot, where the highest value is indicated by the darkest color, which corresponds to the largest number of mobile sensors.

IDEFICS 2: Not Applicable.





GPT-40: Not Applicable

Claude 3 Sonnet: Not Applicable

Reka Core: The subplot at row 5 and column 3 corresponds to the supernova labeled "14C lb". The continuous legend in this subplot is represented by the colorbar on the right side of the figure, which ranges from 0 to 1. The maximum value of the tick labels on this colorbar is 1.

InternVL Chat V1.5: The maximum value of the tick labels on the continuous legend (i.e., colorbar) for the subplot at row 5 and column 3 is 30.

MGM HD Yi 34B: The subplot at row 5 and column 3 is labeled "09fj lb". The continuous legend (colorbar) for this subplot has tick labels ranging from 0.4 to 0.8. The maximum value of the tick labels on the continuous legend is 0.8.

IDEFICS 2: 1.6.

U.27 Example 27



GPT-40: Increases.

Claude 3 Sonnet: The general trend of the data for men in the top right subplot is that it increases sharply from left to right across the age range shown.

Reka Core: The general trend of the data from left to right in the subplot at row 1 and column 2 is that the log hazard rate decreases as age increases, reaches a minimum around age 50, and then increases again with age. This is indicative of a U-shaped curve.

InternVL Chat V1.5: increases

MGM HD Yi 34B: The general trend of data from left to right in the subplot at row 1 and column 2 is "increases". This is observed as the hazard rate for both 1885 and 1905 data points rises with age, indicating a higher risk of death as age increases.

IDEFICS 2: Increases.

U.28 Example 28



GPT-40: To determine the total number of explicitly labeled ticks across all axes in the given plot, we need to count the labeled ticks on both the x-axis and the y-axis.

1. **X-axis (Degree):** - The labeled ticks are: 0, 50, 100, 150, 200, 250, 300 - Total labeled ticks on the x-axis: 7

2. **Y-axis (Proportion of papers):** - The labeled ticks are: 0.00, 0.10, 0.20, 0.30, 0.40 - Total labeled ticks on the y-axis: 5

Adding these together, the total number of explicitly labeled ticks across all axes is:

7 (x-axis) + 5 (y-axis) = 12

So, the total number of explicitly labeled ticks across all axes is 12.

Claude 3 Sonnet: The total number of explicitly labeled ticks across all axes in the given plot is 7. There is one axis labeled "Degree" with ticks at 0, 50, 100, 150, 200, 250, and 300.

Reka Core: The total number of explicitly labeled ticks across all axes in the current plot is 11. This includes the x-axis, which has 7 labeled ticks from 0 to 300 in increments of 50, and the y-axis, which has 5 labeled ticks from 0.00 to 0.40 in increments of 0.05. There are no additional subplots or shared axes in this single plot.

InternVL Chat V1.5: 6

MGM HD Yi 34B: The total number of explicitly labeled ticks across all axes in the current plot is 10. This includes the 5 ticks on the x-axis and the 5 ticks on the y-axis. There are no shared axes or subplots in this image, so the count is straightforward.

IDEFICS 2: 3.

U.29 Example 29



GPT-40: The layout of the subplots is 4 by 1.

Claude 3 Sonnet: The layout of the subplots in the given image is 6 by 1, meaning there are 6 rows and 1 column of subplots.

Reka Core: The image contains a grid of subplots arranged in a 3 by 3 format, with three rows and three columns. Each subplot is labeled with a different expectation value, and the plots are color-coded to represent two different methods, DML and C-DML. The x-axis of all subplots is labeled with σ_u , which suggests that the plots are showing the relationship between these expectation values and σ_u . The y-axes vary depending on the subplot, with different scales and units, indicating different metrics being compared.

InternVL Chat V1.5: The layout of the subplots is 4 by 1.

MGM HD Yi 34B: The layout of the subplots is "2 by 3". This means there are two rows and three columns of subplots. Each subplot contains two lines, one red and one blue, representing different data sets or conditions.

IDEFICS 2: 1 by 5.

U.30 Example 30



V Common Failure Cases of Reasoning Questions

We provide 30 examples that demonstrate examples where all representative models fail to provide a correct answer to the reasoning questions. We categorize mistakes into four categories:

- FACT: factual mistakes without Chain-of-Thought reasoning.
- RSN: factual mistakes with Chain-of-Thought reasoning.
- OCR: errors due to incorrect recognition of textual or numerical elements in the chart.
- INST: mistakes due to not following the instructions.

In general, we found that these representative models rarely make OCR or instruction-followingrelated mistakes. Rather, they make factual mistakes with or without Chain-of-Thought (CoT) reasoning. Different models exhibit different behaviors in zero-shot CoT. For example, both GPT-4o and Claude 3 Sonnet generate zero-shot CoT about half of the time, Reka Core and MGM HD Yi 34B always generate zero-shot CoT, and InternVL Chat V1.5 and IDEFICS 2 almost never generate zero-shot CoT. We also found that the CoT process between Reka Core and MGM HD Yi 34B is very similar at times, where they share a significant amount of common prefixes (see Apps. V.7, V.11, V.19, V.25, V.26 and V.29).

Table 22: Overview of failure case examples in reasoning questions. We provide 30 concrete examples within 4 predefined instruction category: TC=Text-in-Chart; TG=Text-in-General; NC=Number-in-Chart; and NG=Number-in-General.

		Proprietary Models			Open-Source Models		
ID	Instruction Category	GPT-40	Claude 3 Sonnet	Reka Core	InternVL Chat V1.5	MGM HD Yi 34B	IDEFICS 2
1	TC	FACT	RSN	RSN	RSN	RSN	FACT
2	TC	FACT	OCR	RSN	OCR	RSN	FACT
3	TG	RSN	RSN	INST	INST	RSN	FACT
4	TG	FACT	RSN	RSN	FACT	RSN	INST
5	NG	RSN	RSN	RSN	FACT	RSN	FACT
6	TC	RSN	RSN	RSN	FACT	RSN	FACT
7	NC	RSN	FACT	RSN	RSN	INST	FACT
8	TC	FACT	RSN	RSN	FACT	RSN	FACT
9	NC	RSN	RSN	RSN	RSN	RSN	FACT
10	TC	FACT	RSN	RSN	RSN	RSN	FACT
11	TC	FACT	FACT	RSN	FACT	RSN	FACT
12	NC	INST	RSN	INST	INST	RSN	INST
13	TC	RSN	RSN	RSN	FACT	RSN	FACT
14	NG	RSN	RSN	RSN	FACT	RSN	FACT
15	NG	RSN	RSN	RSN	FACT	RSN	FACT
16	TC	FACT	FACT	RSN	FACT	RSN	FACT
17	TC	FACT	FACT	RSN	FACT	RSN	FACT
18	TC	FACT	FACT	RSN	FACT	RSN	FACT
19	TC	RSN	RSN	RSN	FACT	RSN	FACT
20	NC	RSN	INST	INST	INST	INST	FACT
21	TC	FACT	RSN	RSN	FACT	RSN	INST
22	NC	FACT	FACT	RSN	FACT	RSN	FACT
23	TC	FACT	FACT	RSN	FACT	RSN	INST
24	NG	RSN	FACT	FACT	FACT	RSN	FACT
25	TC	FACT	RSN	OCR	FACT	OCR	OCR
26	TC	FACT	FACT	RSN	FACT	OCR	OCR
27	NG	RSN	RSN	RSN	FACT	RSN	FACT
28	NG	RSN	FACT	RSN	FACT	RSN	FACT
29	NC	FACT	FACT	RSN	FACT	RSN	FACT
30	TG	FACT	RSN	RSN	INST	RSN	FACT

V.1 Example 1

Example
Area
<pre>Question: Adding up all numbers in each individual column, which column achieves the smallest total value? * Your final answer must be grounded to some text that is explicitly written and relevant to the question in the chart. * If you need to answer multiple terms, separate them with commas. * Unless specified in the question (such as answering with a letter), you are required to answer the full names of subplots and/or labels by default. Answer: DIOE</pre>
GPT-40: The column with the smallest total value is "DICE."
Claude 3 Sonnet : The column that achieves the smallest total value when adding up all the numbers is DICR, which corresponds to the "Informative, Contradict, Reject" condition in the chart.
Reka Core : To find the column with the smallest total value, we need to add up all the numbers in each column and compare the totals. The columns are labeled with combinations of letters and acronyms, which likely stand for different categories or groups within the study. For example, the first column is labeled "DACE," and the last column is labeled "WIOR." We will add the numbers in each column and compare the totals: 1. DACE: $4.5 + 4.6 + 5.3 + 4.8 = 19.2 2$. DACR: $5.6 + 5.6 + 6.6 + 7.9 = 25.7 3$. DAOE: $6.3 + 4.6 + 4.3 + 3.6 = 18.8 4$. DAOR: $10.2 + 9.4 + 13.1 + 6.8 = 39.5 5$. DICE: $0.9 + 0.9 + 1.1 + 0.9 = 3.8 6$. DICR: $1.1 + 1.0 + 1.5 + 1.3 = 4.9 7$. DIOE: $1.1 + 1.9 + 0.7 + 0.7 = 4.4 8$. DIOR: $1.7 + 1.9 + 1.9 + 1.6 = 6.1 9$. WACE: $18.2 + 19.4 + 22.1 + 19.0 = 78.7 10$. WACR: $24.8 + 26.8 + 27.2 + 29.2 = 107.0 11$. WAOE: $27.1 + 34.4 + 26.9 + 25.2 = 113.6 12$. WAOR: $34.9 + 35.0 + 36.7 + 32.9 = 139.5 13$. WICE: $14.6 + 15.0 + 16.4 + 17.9 = 63.9 14$. WICR: $15.2 + 11.2 + 18.8 + 19.2 = 64.4 15$. WIOE: $19.6 + 18.5 + 19.0 + 16.0 = 72.1 16$. WIOR: $24.2 + 18.5 + 24.5 + 23.4 = 90.6$ Comparing the totals, the column with the smallest total value is "DICE" with a total of 3.8 .
InternVL Chat V1.5: The column that achieves the smallest total value is the "Cooperative" column.
MGM HD Yi 34B: To determine which column achieves the smallest total value, we need to sum the values in each column. However, the image does not provide a clear numerical value for each cell, and thus we cannot perform an exact calculation. We can only visually estimate the values based on the color intensity and the scale provided on the right side of the chart. By visually inspecting the chart, we can see that the column labeled "Cooperative" has the lightest shades of blue, indicating the lowest values. To confirm this, we would need to add up the visible numbers in each column, but since the exact values are not legible, we cannot provide a precise answer. Therefore, based on the visual information available, the "Cooperative" column appears to have the smallest total value.
IDEFICS 2: DACR.

V.2 Example 2



MGM HD Yi 34B: The label of the y-axis in the subplot where the blue dots form the smallest clusters is "Call". This can be determined by looking at the bottom left subplot, where the blue dots are sparse and do not form large clusters, and the y-axis is clearly labeled with the word "Call".

IDEFICS 2: RV[m/s].

V.3 Example 3



V.4 Example 4



GPT-40: Row 3, Column 2

Claude 3 Sonnet: The subplot where all three quartile curves (Estimated Quantiles, Empirical Quantiles, and Out-of-sample Quantiles) agree the most for quantile levels between 0.2 and 0.8 appears to be row 3, column 2.

Reka Core: The subplot where all three quartile curves agree the most for quartile levels between 0.2 and 0.8 is in row 2, column 2. In this subplot, the lines representing the estimated quantiles, empirical quantiles, and out-of-sample quantiles are almost indistinguishable from each other, indicating a high level of agreement across the specified quartile levels.

InternVL Chat V1.5: Row 1, column 1

MGM HD Yi 34B: The subplot where all three quartile curves agree the most for quartile levels between 0.2 and 0.8 is located in the second row, third column. This is determined by visually inspecting the graphs and identifying the one where the lines representing the estimated, empirical, and out-of-sample quantities are closest together within the specified quartile range.

IDEFICS 2: Portfolio level.

V.5 Example 5



V.6 Example 6



is the only one that crosses the W_H axis at a point where the W_I value is positive, which is not the case for the other lines corresponding to $\lambda = 0.13$ and $\lambda = 0.20$.

InternVL Chat V1.5: ap

MGM HD Yi 34B: The line that is the furthest away from its fi value from the W_H axis is the red line, which represents the "ni" category. This can be determined by visually inspecting the graph and noting the distance between the red line and the red "fi" marker on the W_H axis. The red line extends the furthest to the right compared to the other lines, indicating that it has the greatest deviation from its "fi" value.

IDEFICS 2: Ap.

V.7 Example 7



V.8 Example 8

Example
Store = 0 Store = 1 Store = 2 Store = 3 Store = 5 X+ray MRI CT 100% 0% 00% 0% 00
<pre>Question: What is the category with the least percentage in SDBN for the CT modality? * Your final answer must be grounded to some text that is explicitly written and relevant to the question in the chart. * If you need to answer multiple terms, separate them with commas. * Unless specified in the question (such as answering with a letter), you are required to answer the full names of subplots and/or labels by default. Answer: Score = 1</pre>
GPT-40: SSM
Claude 3 Sonnet : According to the stacked bar chart for the CT modality, the category with the least percentage for SDBN (Subdural Hematoma) is $Score = 0$.
Reka Core : The category with the least percentage in SDBN for the CT modality is Score = 5, which has 0%. This can be determined by examining the CT modality's SDBN (SDBN) bar and noting that the topmost segment, which represents Score = 5, is not present, indicating a 0% value.
InternVL Chat V1.5: Score = 0
MGM HD Yi 34B : The category with the least percentage in SDBN for the CT modality is "Score = 0," which has a 20% value.

IDEFICS 2: SSM.

V.9 Example 9



V.10 Example 10



V.11 Example 11



IDEFICS 2: Onewall.

particular measure.

V.12 Example 12

Example RTTS RTTS Question: At an Objectness Threshold of 0.9, how many False Negative Detections are there for IA-Yolo in the ExDark dataset? * Your final answer must be grounded to a number that is exlicitly written and relevant to the question in the chart, even if it 's an approximate value. * You are allowed to extract numbers within some text when needed. Answer: 6000 **GPT-40**: At an Objectness Threshold of 0.9, the number of False Negative Detections for IA-Yolo in the ExDark dataset is approximately 3000. Claude 3 Sonnet: According to the chart for the ExDark dataset, at an Objectness Threshold of 0.9, the number of False Negative Detections for IA-Yolo is approximately 2000. Reka Core: At an Objectness Threshold of 0.9 in the ExDark dataset, the graph shows that IA-Yolo has approximately 2500 False Negative Detections. This is determined by looking at the red line in the middle graph of the ExDark section, where the y-axis represents the number of False Negative Detections and the x-axis represents the Objectness Threshold. The value at 0.9 on the x-axis aligns with the red line at around 2500 on the y-axis. InternVL Chat V1.5: At an Objectness Threshold of 0.9, there are approximately 3000 False Negative Detections for IA-Yolo in the ExDark dataset. MGM HD Yi 34B: At an Objectness Threshold of 0.9, the number of False Negative Detections for IA-Yolo in the ExDark dataset is approximately 2000. This value is read from the y-axis of the False Negatives graph in the ExDark dataset, where the red line representing IA-Yolo intersects with the x-axis at the 0.9 mark.

IDEFICS 2: 5000.

V.13 Example 13



MGM HD Yi 34B: The category with the lowest win rate for the majority of the subplots is "Others," as indicated by the red segments of the bars in the "%(c) Rate" column. This is evident in all three subplots ("Total," "Reco Object," and "Attribute") where the red segments are consistently the shortest, indicating the lowest percentage of win rate compared to the other categories.

IDEFICS 2: Others.

V.14 Example 14



V.15 Example 15



GPT-40: To determine how many intrinsic variability points have ΔNPS values worse than -9%, we need to count the number of points on the graph where the ΔNPS value is less than -9%. From the graph, we can see the following points with their corresponding ΔNPS values: - At ±0, ΔNPS is 0% - At ±2, ΔNPS is approximately -4% - At ±4, ΔNPS is approximately -8% - At ±6, ΔNPS is approximately -10% - At ±8, ΔNPS is approximately -7% - At ±10, ΔNPS is approximately -6% The points with ΔNPS values worse than -9% are: - At ±6, ΔNPS is approximately -10% There is only 1 point where the ΔNPS value is worse than -9%. Therefore, the exact integer answer is 1.

Claude 3 Sonnet: To determine how many intrinsic variability points have Δ NPS values worse than -9%, I will go through the data points and count the number of times the Δ NPS value is less than -9. Intrinsic variability 0: Δ NPS = 0.0, which is not < -9, so count is 0 Intrinsic variability 2: Δ NPS = -7.0, which is not < -9, so count is still 0 Intrinsic variability 4: Δ NPS = -9.0, which is not < -9, so count is still 0 Intrinsic variability 4: Δ NPS = -9.0, which is not < -9, so count is still 0 Intrinsic variability 6: Δ NPS = -10.0, which is < -9, so count is now 1 Intrinsic variability 8: Δ NPS = -5.0, which is not < -9, so count is still 1 Intrinsic variability 10: Δ NPS = -2.0, which is not < -9, so count is still 1 So there is 1 intrinsic variability point that has a Δ NPS value worse than -9%.

Reka Core: To determine the number of intrinsic variability points with Δ NPS values worse than -9%, we look at the y-axis where Δ NPS is plotted and find the -9% mark. Then, we observe the data points on the graph that fall below this line. There are three points that have Δ NPS values below -9%: one at +2 intrinsic variability, one at +4, and one at +6. Therefore, the answer is 3.

InternVL Chat V1.5: two

MGM HD Yi 34B: There are two intrinsic variability points that have Δ NPS values worse than -9%. These points are located at the beginning of the graph, corresponding to the intrinsic variability values of +0 and +2.

IDEFICS 2: 0.





MGM HD Yi 34B: The decile that shows the largest count in the 0%-5% category is the 1st decile. This is determined by visually inspecting the bar chart and identifying the bar corresponding to the 0%-5% category that is the tallest. The 1st decile's bar reaches the highest point on the y-axis compared to the other deciles in the same category.

IDEFICS 2: 1st.
V.17 Example 17



Reka Core: The country that shows a significant bounce in excess Google searches for "cough," "fever," and "sick" shortly after April is Italy. This can be inferred from the graph on the right, where the line representing Italy dips in early April and then rises sharply again, peaking just after the middle of April. The graph indicates that Italy's excess Google searches for these terms were at their lowest in early April, then increased dramatically, suggesting a possible resurgence in interest or concern related to these symptoms, which could be associated with a health event such as a disease outbreak.

InternVL Chat V1.5: Italy

MGM HD Yi 34B: The country that has a significant bounce for Eccess Google searches of "cough," "fever," and "sick" shortly after April is Italy. This is indicated by the pink line on the graph, which shows a sharp increase in the percentage of searches for these terms in the month of April.

IDEFICS 2: Italy.

V.18 Example 18



IDEFICS 2: AT.

Example
Linear DLM Casi-DLM Linear Log Log Log Log Log Log Log Log
<pre>Question: What is the name of the model in which the percentage of US is the largest across all the models? * Your final answer must be grounded to some text that is explicitly written and relevant to the question in the chart. * If you need to answer multiple terms, separate them with commas. * Unless specified in the question (such as answering with a letter), you are required to answer the full names of subplots and/or labels by default. Answer: Misalignment</pre>
Note: even if we don't consider "Misalignment" as a model, the answer should be "Quad," which still yields 0% accuracy among all models.
GPT-40 : The name of the model in which the percentage of the United States is the largest across all the models is "Linear." This is explicitly shown in the chart where the United States has a percentage of 78% in the Linear model.
Claude 3 Sonnet : According to the chart, the model in which the percentage of profits shifted out for the United States is the largest across all models is Log.
Reka Core: The model in which the percentage of US is the largest across all the models is the "Log" model, with a percentage of 62%. This can be determined by looking at the color-coded legend on the right side of the image, which indicates the percentage of profits shifted out or in, and then finding the corresponding color on the US row in the matrix. The "Log" model's cell for the US is the darkest shade of red, which corresponds to the 62% value on the legend.
InternVL Chat V1.5: Log
MGM HD Yi 34B : The name of the model in which the percentage of the United States is the largest across all the models is the "Quad-DLM" model. This can be determined by observing the length of the bars corresponding to the United States in each of the five models. The "Quad-DLM" model has the longest bar for the United States, indicating the highest percentage of profits shifted out.
IDEFICS 2: Log.

V.20 Example 20



V.21 Example 21



InternVL Chat V1.5: Economics and Law

MGM HD Yi 34B: The two majors where the vast majority of students finish their degree in their 5th year are Economics and Engineering. In Economics, 95.5% of students complete their degree in the 5th year, and in Engineering, 94.0% of students do the same. These percentages are significantly higher than those of the other majors, which have lower percentages of students completing in the 5th year.

IDEFICS 2: Law engineering medicine.

V.22 Example 22



MGM HD Yi 34B: The first year in which the Survey of Consumer Finances reports data is 1989. This is indicated by the first data point on the graph for the orange line, which represents the Survey of Consumer Finances.

IDEFICS 2: 1910.

V.23 Example 23



MGM HD Yi 34B: The line that has the second largest value when θ equals 1 in the "Multiplicative risk" graph is the solid black line, which represents the subsidy for the productive player. In the "Winner-only risk" graph, the line with the second largest value at θ equals 1 is the dashed purple line, which represents the subsidy for the competitor.

IDEFICS 2: Winner-only risk.

V.24 Example 24



GPT-40: To determine how many arrows show a positive change in both the Supply-centric index and Demand-centric index, we need to count the arrows that point towards the upper right direction. 1. Start from the bottom left and move to the top right. 2. Count the arrows that are pointing upwards and to the right.

Let's count: 1. The arrow in the bottom left quadrant is pointing downwards and to the left (negative change in both indices). 2. The arrow in the middle left quadrant is pointing to the right (positive change in Demand-centric index only). 3. The arrow in the upper left quadrant is pointing to the right (positive change in Demand-centric index only). 4. The arrow in the middle left quadrant is pointing to the right (positive change in Demand-centric index only). 5. The arrow in the middle left quadrant is pointing upwards and to the right (positive change in both indices). 6. The arrow in the upper right quadrant is pointing upwards and to the right (positive change in both indices). 7. The arrow in the upper right quadrant is pointing upwards and to the right (positive change in both indices). 8. The arrow in the upper right quadrant is pointing upwards and to the right (positive change in both indices). 8. The arrow in the upper right quadrant is pointing upwards and to the right (positive change in both indices). 8. The arrow in the upper right quadrant is pointing upwards and to the right (positive change in both indices). 8. The arrow in the upper right quadrant is pointing upwards and to the right (positive change in both indices). 8. The arrow in the upper right quadrant is pointing upwards and to the right (positive change in both indices). 8. The arrow in the upper right quadrant is pointing upwards and to the right (positive change in both indices).

There are 4 arrows that show a positive change in both the Supply-centric index and Demand-centric index. The exact integer answer is 4.

Claude 3 Sonnet: There are 3 arrows that show a positive change in both the Supply-centric index (pointing upwards) and the Demand-centric index (pointing towards the right) simultaneously.

Reka Core: There are 5 arrows that show a positive change in both the Supply-centric index and Demandcentric index. These are the arrows that point upwards to the right, starting from a position in the lower left quadrant and ending in the upper right quadrant.

InternVL Chat V1.5: 3

MGM HD Yi 34B: To determine the number of arrows showing a positive change in both the Supplycentric index and Demand-centric index, we need to count the arrows that point upwards in both dimensions. Upon examining the graph, there are three arrows that meet this criterion: one in the top left quadrant, one in the top right quadrant, and one in the bottom right quadrant. Therefore, the answer is three.

IDEFICS 2: 1.

V.25 Example 25



IDEFICS 2: Firing (yr).

117





V.27 Example 27



V.28 Example 28



So, the exact integer answer is 18.

Claude 3 Sonnet: According to the scatter plot, there are 4 blue "+" markers representing "Serviced K users" that have a value on the y-axis (meters) less than 5.

Reka Core: There are 3 Serviced K users with a meters value less than 5. This can be determined by counting the number of red crosses (representing Serviced K users) that are positioned to the left of the 5 meters line on the horizontal axis.

InternVL Chat V1.5: 5

MGM HD Yi 34B: To determine the number of Serviced K users with meters values less than 5, we need to count the blue plus signs that are positioned below the 5 mark on the y-axis. Upon examining the graph, there are 10 blue plus signs that fall below the 5 mark. Therefore, the answer is 10.

IDEFICS 2: 1.

V.29 Example 29



IDEFICS 2: 1.

V.30 Example 30



GPT-40: [100, 200]

Claude 3 Sonnet: Based on the graph, the interval where the area enclosed by the curve and the x-axis appears to be the largest is [0, 100]. This interval contains the high spikes or overshoots in the signal power, resulting in a significantly larger area under the curve compared to the other intervals shown.

Reka Core: The area enclosed by the curve and the x-axis in a graph represents the integral of the function over that interval, which in this context can be interpreted as the total energy delivered over that time period. By visually inspecting the graph, the largest area under the curve is between the samples 0 and 100, where the active power starts at 0 W, rises sharply to an overshoot, and then falls to a stable value. This interval shows the greatest initial energy delivery, which is not surpassed by any subsequent intervals shown in the graph. So the answer is [0, 100].

InternVL Chat V1.5: The area enclosed by the curve and the x-axis is the same across all intervals.

MGM HD Yi 34B: The area enclosed by the curve and the x-axis can be interpreted as the total active power over a given interval. The largest area is observed in the interval [0, 100], where the curve starts at the lowest point on the graph and rises sharply to the peak labeled "Overshoot." This indicates that the most active power is accumulated in this initial interval, which is consistent with the behavior of a system that experiences a rapid increase in power output before stabilizing.

IDEFICS 2: [0, 100].

W Datasheets for Datasets

This document is based on *Datasheets for Datasets* by Gebru et al. [23]⁸

W.1 Motivation

For what purpose was the dataset created? Was there a specific task in mind? Was there a specific gap that needed to be filled? Please provide a description.

The dataset is created to evaluate multimodal large language models on a more diverse and realistic set of charts and questions (see §3). The specific gap to be filled is the lack of diverse chart and questions in existing evluation datasets, which often lead to an overestimation of open-source model's performance (see §2).

Who created this dataset (e.g., which team, research group) and on behalf of which entity (e.g., company, institution, organization)?

All chart selections and QA annotations were curated by graduate students from Princeton University. Chart creators are credited to authors of the selected arXiv preprints.

What support was needed to make this dataset? (e.g. who funded the creation of the dataset? If there is an associated grant, provide the name of the grantor and the grant name and number, or if it was supported by a company or government agency, give those details.)

This work is supported by the Accelerate Foundation Models Academic Research Initiative from Microsoft. Mengzhou Xia is supported by an Apple Scholars in AIML Fellowship. Luxi He is supported by the Gordon Wu Fellowship.

Any other comments? N/A

W.2 Composition

What do the instances that comprise the dataset represent (e.g., documents, photos, people, countries)? Are there multiple types of instances (e.g., movies, users, and ratings; people and interactions between them; nodes and edges)? Please provide a description.

The dataset consists of images that are all charts sourced from arXiv preprints and texts that are questions and answers curated by our annotators.

How many instances are there in total (of each type, if appropriate)?

CharXiv contains 2,323 charts, 19 unique descriptive questions and 2,323 unique reasoning questions in total. Each chart is paired with 4 descriptive questions and 1 reasoning question. Each question is paired with a clear short answer. More details are shown in Tab. 2.

Does the dataset contain all possible instances or is it a sample (not necessarily random) of instances from a larger set? If the dataset is a sample, then what is the larger set? Is the sample representative of the larger set (e.g., geographic coverage)? If so, please describe how this representativeness was validated/verified. If it is not representative of the larger set, please describe why not (e.g., to cover a more diverse range of instances, because instances were withheld or unavailable).

It contains a sample of instances from all figures in arXiv papers. In particular, we constrain the date of the preprints within 2020-2023 as we found that figures in earlier years are not as complex and diverse as figures in more recent years. Further, all figures have to be charts to be included in CharXiv. The decisions are to comply with the purpose of CharXiv.

⁸We use the template from the following codebase: https://github.com/AudreyBeard/ Datasheets-for-Datasets-Template.

What data does each instance consist of? "Raw" data (e.g., unprocessed text or images) or features? In either case, please provide a description.

Each chart instance is re-rendered from vector-based files (*e.g.*, PDF, EPS, SVG) to jpeg files wherever possible. We resize all images such that its longer side has a length of 1024px. All texts are raw data.

Is there a label or target associated with each instance? If so, please provide a description. Each chart comes with 4 descriptive questions and 1 reasoning question. Every question has a ground truth answer.

Is any information missing from individual instances? If so, please provide a description, explaining why this information is missing (e.g., because it was unavailable). This does not include intentionally removed information, but might include, e.g., redacted text. Not Applicable.

Are relationships between individual instances made explicit (e.g., users' movie ratings, social network links)? If so, please describe how these relationships are made explicit. Yes, all charts can be traced back to the original preprint assets by their arXiv identifiers which are part of our metadata.

Are there recommended data splits (e.g., training, development/validation, testing)? If so, please provide a description of these splits, explaining the rationale behind them.

Yes, we randomly split the entire dataset of 2,323 charts with their questions into 1,000 charts as the validation set and 1,323 charts as the test set. As a benchmark, we do not have a training set, and our data is never intended to be used as a training set. The size (1,000) of the validation set is to ensure that the variance is small in comparing model performance.

Are there any errors, sources of noise, or redundancies in the dataset? If so, please provide a description.

All QAs are validated by humans, and thus we do not expect errors. If errors exist, the sources of noise come from human annotation. There is no redundancy in the dataset.

Is the dataset self-contained, or does it link to or otherwise rely on external resources (e.g., websites, tweets, other datasets)? If it links to or relies on external resources, a) are there guarantees that they will exist, and remain constant, over time; b) are there official archival versions of the complete dataset (i.e., including the external resources as they existed at the time the dataset was created); c) are there any restrictions (e.g., licenses, fees) associated with any of the external resources that might apply to a future user? Please provide descriptions of all external resources and any restrictions associated with them, as well as links or other access points, as appropriate. It is self-contained.

Does the dataset contain data that might be considered confidential (e.g., data that is protected by legal privilege or by doctor-patient confidentiality, data that includes the content of individuals' non-public communications)? If so, please provide a description. No.

Does the dataset contain data that, if viewed directly, might be offensive, insulting, threatening, or might otherwise cause anxiety? If so, please describe why. No.

Does the dataset relate to people? If not, you may skip the remaining questions in this section. No.

Does the dataset identify any subpopulations (e.g., by age, gender)? If so, please describe how these subpopulations are identified and provide a description of their respective distributions within the dataset.

Is it possible to identify individuals (i.e., one or more natural persons), either directly or indirectly (i.e., in combination with other data) from the dataset? If so, please describe how. No.

Does the dataset contain data that might be considered sensitive in any way (e.g., data that reveals racial or ethnic origins, sexual orientations, religious beliefs, political opinions or union memberships, or locations; financial or health data; biometric or genetic data; forms of government identification, such as social security numbers; criminal history)? If so, please provide a description.

No.

Any other comments? N/A

W.3 Collection

How was the data associated with each instance acquired? Was the data directly observable (e.g., raw text, movie ratings), reported by subjects (e.g., survey responses), or indirectly inferred/derived from other data (e.g., part-of-speech tags, model-based guesses for age or language)? If data was reported by subjects or indirectly inferred/derived from other data, was the data validated/verified? If so, please describe how.

Charts are collected from source files of arXiv preprints that are publicly available and are further processed and annotated. Questions are constructed with human annotations.

Over what timeframe was the data collected? Does this timeframe match the creation timeframe of the data associated with the instances (e.g., recent crawl of old news articles)? If not, please describe the timeframe in which the data associated with the instances was created. Finally, list when the dataset was first published.

Chart data was collected in November 2023. Charts in CharXiv are from preprints between 2020 and 2023. Questions were annotated in April 2024.

What mechanisms or procedures were used to collect the data (e.g., hardware apparatus or sensor, manual human curation, software program, software API)? How were these mechanisms or procedures validated?

We follow arXiv's instructions to bulk-download data from their data storage from AWS S3. The rest of the data collection and curation process is discussed in §3.

What was the resource cost of collecting the data? (e.g. what were the required computational resources, and the associated financial costs, and energy consumption - estimate the carbon footprint.) There is no direct cost associated with data collection as all charts are manually selected by humans, and all questions and answers are manually curated by humans. Indirect cost may include bulk-downloading source files from arXiv, which cost \$350 and generating candidate QAs in data annotation process, which cost around \$500.

If the dataset is a sample from a larger set, what was the sampling strategy (e.g., deterministic, probabilistic with specific sampling probabilities)?

Manual Rules (*e.g.*, figures have to be charts that come from preprints in specific years with a specific cosine similarity compared to some image embeddings). The rest follow a random sampling (with a seed to ensure reproducibility).

Who was involved in the data collection process (e.g., students, crowdworkers, contractors) and how were they compensated (e.g., how much were crowdworkers paid)?

No.

Graduate students are involved in the data collection process and they are not compensated.

Were any ethical review processes conducted (e.g., by an institutional review board)? If so, please provide a description of these review processes, including the outcomes, as well as a link or other access point to any supporting documentation. No.

Does the dataset relate to people? If not, you may skip the remainder of the questions in this section.

No.

Did you collect the data from the individuals in question directly, or obtain it via third parties or other sources (e.g., websites)?

Chart data is collected from preprints in arXiv servers that are publicly available. All questions are new and manually curated by our human annotators.

Were the individuals in question notified about the data collection? If so, please describe (or show with screenshots or other information) how notice was provided, and provide a link or other access point to, or otherwise reproduce, the exact language of the notification itself. N/A

Did the individuals in question consent to the collection and use of their data? If so, please describe (or show with screenshots or other information) how consent was requested and provided, and provide a link or other access point to, or otherwise reproduce, the exact language to which the individuals consented.

N/A

If consent was obtained, were the consenting individuals provided with a mechanism to revoke their consent in the future or for certain uses? If so, please provide a description, as well as a link or other access point to the mechanism (if appropriate) N/A

Has an analysis of the potential impact of the dataset and its use on data subjects (e.g., a data protection impact analysis)been conducted? If so, please provide a description of this analysis, including the outcomes, as well as a link or other access point to any supporting documentation. No. Our data are intended to be used in evaluation only and all charts are publicly avialable.

Any other comments? N/A

W.4 Preprocessing / Cleaning / Labeling

Was any preprocessing/cleaning/labeling of the data done(e.g., discretization or bucketing, tokenization, part-of-speech tagging, SIFT feature extraction, removal of instances, processing of missing values)? If so, please provide a description. If not, you may skip the remainder of the questions in this section.

All figures are re-rendered, resized, and manually screened to be charts. All questions are manually curated. More details are in §3.

Was the "raw" data saved in addition to the preprocessed/cleaned/labeled data (e.g., to support unanticipated future uses)? If so, please provide a link or other access point to the "raw" data. Raw data is available in arXiv servers and we provide relative directory to the original asset for every chart in CharXiv.

Is the software used to preprocess/clean/label the instances available? If so, please provide a link or other access point.

We use LabelStudio [79] to annotate the data.

Any other comments? N/A

W.5 Uses

Has the dataset been used for any tasks already? If so, please provide a description. CharXiv is not a repurposed dataset, although possible overlapping data can be observed in SciCap [28], SciGraphQA [47] and Multimodal Arxiv [46].

Is there a repository that links to any or all papers or systems that use the dataset? If so, please provide a link or other access point. Yes, https://charxiv.github.io

What (other) tasks could the dataset be used for?

The dataset is solely used to evaluate models in open-vocabulary chart understanding.

Is there anything about the composition of the dataset or the way it was collected and preprocessed/cleaned/labeled that might impact future uses? For example, is there anything that a future user might need to know to avoid uses that could result in unfair treatment of individuals or groups (e.g., stereotyping, quality of service issues) or other undesirable harms (e.g., financial harms, legal risks) If so, please provide a description. Is there anything a future user could do to mitigate these undesirable harms?

Charts come from preprints between 2020 and 2023. Therefore, they may become outdated if visual representations of the charts change significantly in future.

Are there tasks for which the dataset should not be used? If so, please provide a description. The dataset should not be used to train models.

Any other comments? N/A

W.6 Distribution

Will the dataset be distributed to third parties outside of the entity (e.g., company, institution, organization) on behalf of which the dataset was created? If so, please provide a description. Yes, anyone can publicly use CharXiv to evaluate models for research purposes.

How will the dataset will be distributed (e.g., tarball on website, API, GitHub)? Does the dataset have a digital object identifier (DOI)?

QA pairs will be distributed on GitHub while charts will be distributed on HuggingFace. We do not plan to add a DOI.

When will the dataset be distributed? June 2024

Will the dataset be distributed under a copyright or other intellectual property (IP) license, and/or under applicable terms of use (ToU)? If so, please describe this license and/or ToU, and provide a link or other access point to, or otherwise reproduce, any relevant licensing terms or ToU, as well as any fees associated with these restrictions.

All charts are subjected to their respective copyrights by the authors from their arXiv preprints. We

impose CC BY-SA 4.0 on all the questions and answers that we created.

Have any third parties imposed IP-based or other restrictions on the data associated with the instances? If so, please describe these restrictions, and provide a link or other access point to, or otherwise reproduce, any relevant licensing terms, as well as any fees associated with these restrictions.

All charts are subjected to their respective copyrights by the authors from their arXiv preprints.

Do any export controls or other regulatory restrictions apply to the dataset or to individual instances? If so, please describe these restrictions, and provide a link or other access point to, or otherwise reproduce, any supporting documentation. N/A

Any other comments? N/A

W.7 Maintenance

Who is supporting/hosting/maintaining the dataset? Authors of CharXiv are supporting, hosting, and maintaining the dataset.

How can the owner/curator/manager of the dataset be contacted (e.g., email address)? zw1300@cs.princeton.edu

Is there an erratum? If so, please provide a link or other access point. This is the initial release of CharXiv and we will update CharXiv with erratum in the future under https://charxiv.github.io

Will the dataset be updated (e.g., to correct labeling errors, add new instances, delete instances)? If so, please describe how often, by whom, and how updates will be communicated to users (e.g., mailing list, GitHub)?

Yes, we will update the dataset every 3-6 months by authors of CharXiv and the updates will be included in GitHub.

If the dataset relates to people, are there applicable limits on the retention of the data associated with the instances (e.g., were individuals in question told that their data would be retained for a fixed period of time and then deleted)? If so, please describe these limits and explain how they will be enforced. N/A

Will older versions of the dataset continue to be supported/hosted/maintained? If so, please describe how. If not, please describe how its obsolescence will be communicated to users. N/A (we haven't decided).

If others want to extend/augment/build on/contribute to the dataset, is there a mechanism for them to do so? If so, please provide a description. Will these contributions be validated/verified? If so, please describe how. If not, why not? Is there a process for communicating/distributing these contributions to other users? If so, please provide a description.

Yes, all data are publicly accessible and we also provide contact access to managers of CharXiv. All the QAs are licensed in CC BY-SA 4.0 which allows adaptation and remix.

Any other comments? N/A

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URL to benchmark. The benchmark URL can be found here: https://charxiv.github.io

URL to Croissant metadata. The Croissant metadata URL can be found here: https://huggingface.co/datasets/princeton-nlp/CharXiv/blob/main/croissant.json

Author statement & license information. We the authors bear all responsibility in case of violation of rights. All charts are subjected to their respective copyrights by the authors from their arXiv preprints. All QAs are licensed under CC BY-SA 4.0. Our code is licensed under Apache 2.0.

Hosting and maintenance. We have a dedicated GitHub page to host the leaderboard (https://charxiv.github.io) while data and codebase will be hosted on Huggingface (https://huggingface.co/princeton-nlp/CharXiv) and GitHub (https://github.com/princeton-nlp/CharXiv). We are committed to performing major maintenance on CharXiv every 3-6 months.

Dataset Structure. We separately store charts and questions. Anyone who needs to use CharXiv needs to download the charts from our HuggingFace repository and deflate the zipped contents into the images folder of our codebase. The deflated contents contain 2,323 images in jpg format. In the data folder, we provide all json files that store metadata, questions and answers for each chart with _val and _test postfix to distinguish the validation and the test set. image_metadata file contains mapping from the chart to its year, subject, original path (*i.e.*, the relative directory of the bulk-downloaded contents from arXiv servers), caption, preprint identifier, and title (of the preprint). descriptive contains mapping from the chart to its number of subplots, descriptive questions, and answers. reasoning contains mapping from the chart to the reasoning question and the answer with answer type and question source. In addition, constants.py in the root directory contains mapping from descriptive question number to the descriptive questions themselves, response generation instructions and grading instructions for each descriptive question and each type of reasoning questions.