

ChartX & ChartVLM: A Versatile Benchmark and Foundation Model for Complicated Chart Reasoning

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Abstract

Recently, many versatile Multi-modal Large Language Models (MLLMs) have emerged continuously. However, their capacity to query information depicted in visual charts and engage in reasoning based on the queried contents remains under-explored. In this paper, to comprehensively and rigorously benchmark the ability of the off-the-shelf MLLMs in the chart domain, we construct ChartX, a multi-modal evaluation set covering 18 chart types, 7 chart tasks, 22 disciplinary topics, and high-quality chart data. Besides, we develop ChartVLM to offer a new perspective on handling multi-modal tasks that strongly depend on interpretable patterns, such as reasoning tasks in the field of charts or geometric images. We evaluate the chart-related ability of mainstream MLLMs and our ChartVLM on the proposed ChartX evaluation set. Extensive experiments demonstrate that ChartVLM surpasses both versatile and chart-related large models, achieving results comparable to GPT-4V. We believe that our study can pave the way for further exploration in creating a more comprehensive chart evaluation set and developing more interpretable multi-modal models. Both ChartX and ChartVLM are available at: <https://github.com/UniModal4Reasoning/ChartVLM>

1 Introduction

Versatile Multi-modal Large Language Models (MLLMs) have made promising progress in general-purpose vision-language applications such as multi-modal Question Answering (QA) [17, 3, 33, 21], embodied AI [11], and mathematical reasoning [32, 36, 12]. Although MLLMs have demonstrated their powerful generalization ability in a wide range of multi-modal tasks, their performance in multi-modal reasoning tasks still falls short of human abilities [37, 5, 1]. For instance, humans can easily extract numerical values from a given visual chart and engage in a series of complicated logical reasoning based on the extracted values. However, at present, the MLLMs’ ability to perform complicated logical reasoning based on chart data has not been fully explored.

In this paper, to further validate their capabilities in more complicated reasoning tasks involving chart data, we propose a multi-modal benchmark for comprehensive chart understanding. As illustrated in Fig. 1, our work comprises two contributions: (1) ChartX, which is a comprehensive, high-quality evaluation set designed to sufficiently assess the chart understanding abilities of the off-the-shelf MLLMs, and (2) An interpretable Chart-domain Vision-Language Model (ChartVLM) for general-purpose chart applications.

To construct a comprehensive chart evaluation set, we collected 48K multi-modal chart data covering 22 topics, 18 chart types, and 7 tasks. Each chart data within this dataset includes four modalities,

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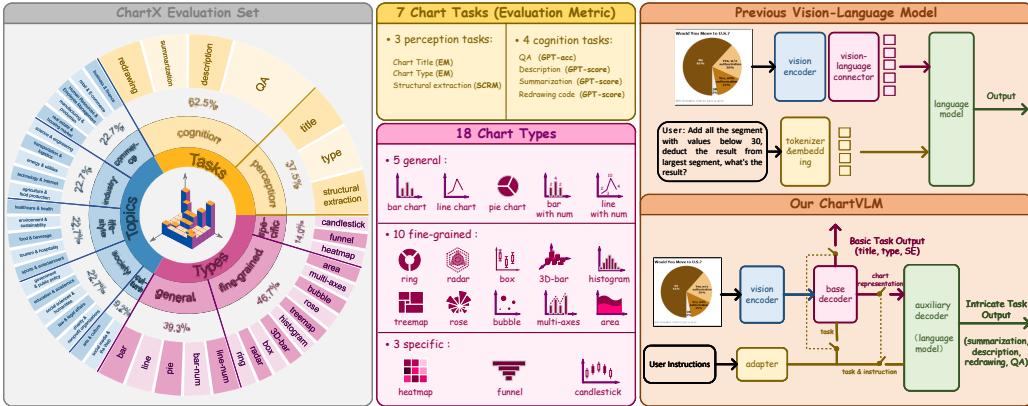


Figure 1: Our work offers two insights: **a)** ChartX: a comprehensive multi-modal chart evaluation set encompassing 22 disciplinary topics, 18 chart types, and 7 tasks where models are evaluated using task-specific metrics such as EM, GPT-acc GPT-score, SCRM [34], and **b)** ChartVLM: a novel framework to perform the multi-tasks in the chart domain. Our key point is to leverage the instruction adapter to dynamically choose the task that needs to be executed. For downstream tasks that rely on querying chart information, we prioritize chart structural extraction before engaging in chart reasoning tasks. This sequence aims to enhance the interpretability of the reasoning results.

including image, Comma-Separated Values (CSV), python code, and text description. According to the task complexity, we classify the proposed 7 chart tasks into two general categories: perception tasks (chart structural extraction, chart type classification, and chart title extraction) and cognition tasks (QA, chart description, chart summarization, and chart re-drawing).

For certain scientific domains such as chart reasoning, where interpretability is paramount, our primary observation is prioritizing the perception tasks before engaging in the complicated reasoning tasks. The statistical information extracted via the perception tasks plays a pivotal role in providing essential support for the interpretability of the model’s reasoning tasks. Building upon this observation, we introduce ChartVLM, characterized by the integration of perception task predictions (*e.g.*, structural data extraction) into reasoning tasks to enhance the interpretability of the reasoning results. Furthermore, ChartVLM utilizes an instruction adapter to dynamically select tasks that users expect to perform according to the users’ instructions, ensuring both interpretability and interactivity concurrently.

On top of this, the existing open-source chart datasets are consolidated for the training of ChartVLM, including ChartQA [23], Chart-to-text [26], PlotQA [25], and SimChart9K [34]. Note that during the training process, ChartVLM has no access to any data from the ChartX evaluation set. Then, we conduct comprehensive comparisons of ChartVLM with current MLLMs [3, 21] on the ChartX evaluation set, including base abilities, *e.g.*, data extraction, and advanced abilities, *e.g.*, complicated problem-solving, where we demonstrate the superiority of our ChartVLM.

2 Related Work

Chart Perception aims to extract the numerical and textual information from a given visual chart. By leveraging the OCR tools [22] to supplement the textual information, the basic function of extracting chart information can be achieved. Recently, some researchers [7, 29, 10] have attempted to perform a chart-to-table transformation for the visual chart perception task, by means of self-supervision from image-table pairs. For example, Deplot [18] fine-tuned an image-to-text transformer for such conversion. StructChart [34] utilizes the encoder-decoder framework to achieve transformation. These methods extract the tabular format of a visual chart and leverage the external module such as GPT [28, 4] to perform downstream tasks. However, their chart-related reasoning abilities strongly depend on external modules, whose scalability is hard to guarantee.

Chart Cognition is defined as a process to deal with intricate tasks related to both chart-related knowledge and common sense knowledge. A typical example is to query numerical points from a chart and give the prediction results using mathematical or logical reasoning. Recent studies [8, 31,

Study Works	# Chart Topic	# Chart Type	# Task Type	# Evaluation Chart Images	# Evaluation Dataset	Evaluation Metric	Open-source
<i>Single-task Evaluation</i>							
PlotQA [25]	N/A	3	1	33.7K	PlotQA	EM & AP	✓
Chart-to-text [26]	6	6	1	6.6K	Chart-to-text	EM	✓
ChartQA [23]	15	3	1	1.5K	ChartQA	EM	✓
OpenCQA [15]	10	5	1	1.2K	OpenCQA	EM & BLEU & ROUGE	✓
<i>Multi-task Evaluation</i>							
ChartLlama [6]	N/A	10	7	1.5K	ChartQA & Chart-to-text	EM & GPT	✗
ChartBench [35]	N/A	9	4	2K	ChartBench	Accuracy	✗
MMC [20]	5	6	9	2.1K	MMC	GPT	✗
ChartAssisstant [24]	N/A	9	5	1.5K	CharQA & OpenCQA	EM& BLEU	✗
Ours	22	18	7	6K	ChartX	EM & SCRM & GPT-acc & GPT-score	✓

Table 1: Comparison with the existing chart-related benchmarks, where ChartX is constructed for comprehensively evaluating the off-the-shelf vision-language large models from more chart types and topics. Besides, EM denotes Exact Match and SCRM represents the Structuring Chart-oriented Representation Metric described in StructChart [34].

[38, 16, 19] focus on showing the reasoning ability of their models on chart domain. Pix2Struct [16] presents a pre-training method using masked screenshots from web pages, which is verified to be effective in chart understanding tasks such as ChartQA dataset [23]. Besides, MatCha [23] decodes the answers to chart questions in an end-to-end manner, where the chart reasoning ability can be enhanced from MATH data [30].

Multi-Modal Chart Generation and Benchmark. Chart data generation is a crucial step for scaling up the model ability [31, 19, 2]. Previous chart-related benchmarks only cover general three types of charts (line, pie, bar charts) and focus on a few tasks such as chart-to-table tasks for ChartQA [23], PlotQA [25], and Chart-to-Text [26], and QA tasks for DVQA [13] and OpenCQA [15]. Recently, various benchmarks have been proposed in some works, *e.g.* MMC [20], ChartLlama [6], ChartBench [35], and ChartAssisstant [24], with the common characteristics of more types, more tasks, and more modalities of chart data, which is insightful for the chart community. However, as shown in Table 1, the data and metric diversity of charts used for evaluating multi-modal large models is relatively limited. For example, ChartBench [35] merely uses a two-sided judgment (yes or no) to evaluate model performance. The types of charts and data in MMC [20] are also insufficient in verifying the chart ability of the off-the-shelf MLLMs.

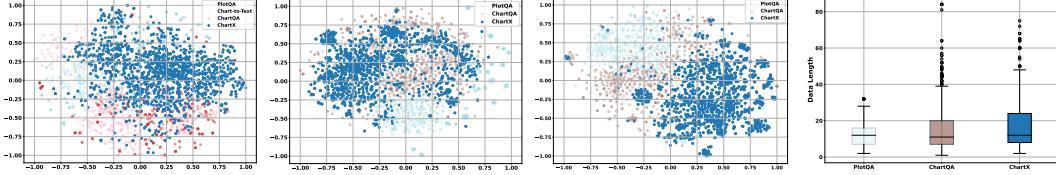
3 ChartX: Multi-task Chart Evaluation Set

3.1 Coverage Analysis of the Evaluation Set

We describe the coverage range of ChartX from chart types, chart topics, and chart-related tasks, respectively.

Chart Types. ChartX covers all chart types where chart data can be directly converted into a structural data format, *e.g.*, CSV format, resulting in a total of more than 18 chart types. For a clear visualization, we categorize different chart types into three groups based on their usage frequency and application fields. **(1) General Chart Types:** bar chart (with or w/o numerical data), line chart (with or w/o numerical data), and pie chart. These five chart types are commonly employed to represent a wide range of chart data distribution. **(2) Fine-grained Chart Types:** ring chart, radar chart, box plot, 3D-bar chart, histogram, treemap, rose chart, bubble chart, multi-axes chart, and area chart. These 10 chart types are mostly variations of the general chart types to present the complex data distribution more vividly. **(3) Domain-specific Chart Types:** heatmap, funnel, and candlestick. These three chart types are specially designed to visualize data distribution within domain-specific fields. For example, heatmap is commonly used to visualize the significant difference trend in a 2D space. Funnel charts are widely used in the analysis of market sales, while candlestick is primarily utilized for depicting stock trends. The distribution statistics of chart type in ChartX are shown in Fig. 1. Specifically, we generate more images on general chart types to expand the chart diversity, which are more frequently utilized with more diversity. For the fine-grained chart types, the image number of each type is balanced to avoid the long-tail distribution issue in our benchmark.

Chart Topics. ChartX contains various chart topics covering as many themes as possible. Specifically, the high-level topics in ChartX can be divided into five perspectives: commerce, industry, society, culture, and lifestyle. And fine-grained topic types can be subdivided into 22 sub-disciplinaries,



(a) Image Distribution. (b) CSV Data Distribution. (c) Question Distribution. (d) Data Length Distribution.
Figure 2: Data Distribution Comparisons, depicting the diversity of (a) chart image, (b) CSV data, (c) questions in QA pairs, and (d) CSV data length.

which are listed in Fig. 1. The topic distribution of ChartX is presented in Fig. 1. More statistical results of chart topics are shown in Appendix A.1.

Chart Tasks. Unlike previous chart benchmarks focusing on the category of visual logic reasoning tasks, the ChartX benchmark emphasizes the interpretability for all downstream chart-related tasks. Given that interpretability relies heavily on the ability to perceive chart information, ChartX categorizes perception-related tasks as base tasks, including title perception, chart type recognition, and Structural Extraction (SE). On the other hand, other chart-related tasks are classified as intricate cognition tasks, including chart-related Question Answering (QA), Chart Description, Chart Summarization, and Chart Redrawing. In the context of ChartX, **QA** refers to answering questions that are formulated solely based on the chart data, requiring reasoning derived directly from the provided chart information. This characteristic distinguishes ChartX from previous chart-related QA datasets like ChartQA [23]. In ChartQA [23], there exists a certain number of QA pairs that cannot be answered solely based on the information presented in the given chart image. **Chart Description** aims at presenting detailed information and some insights from the distribution of chart data, while **Chart Summarization** features summarizing the trend-like or high-level characteristics from the given data in a few sentences. **Chart Redrawing** refers to plotting the given data into a new chart image with the same chart type of original data. The distribution of each task is listed in Fig. 1. For each image, together with labels of base tasks, we collect two QA samples, one description sample, one summarization sample, and one redrawing code sample. Overall, the samples from multi-tasks reach 48K in ChartX.

3.2 Distribution Analysis of the Evaluation Set

We analyze the distribution diversity of the ChartX benchmark by considering both style distribution and content distribution. Fig. 2 visually depicts the diversity comparison among various chart benchmarks using t-SNE.

Style Distribution. In terms of style distribution, the inner-class diversity is considered to augment the style fashion of each chart type. Such diversification is achieved by both package and hyper-parameter diversity performed by human efforts. For each chart type, we design an individual diversification scheme with different plotting package candidates and different hyper-parameter settings. A general alternative plotting scheme includes *matplotlib*, *seaborn*, and *plotly* packages, etc, while some domain-specific packages like *mplfinance* are also employed to increase the diversity. The hyper-parameter diversity involves the adjustment of all possible hyper-parameter settings in plotting, e.g., figure size, background setting, axis/legend location, line, marker style, tick, filling styles, alpha, annotation, etc.

Content Distribution. As for content diversity, the CSV data length distribution and task-wise token distribution for each chart are visualized for different chart benchmarks to compare the content distribution diversity. As shown in Fig. 2, the ChartX benchmark presents a higher diversity in both CSV data length and token distribution than the existing benchmarks.

3.3 Two-stage Chart Data Generation

Utilizing the strong generation capabilities of GPT-4 [1], ChartX is created through an automated online generation process with manual instructions. This involves a data-centric two-stage generation paradigm, encompassing the creation of perception and cognition data.

Data Acquisition: Chart Perception. As mentioned earlier, chart perception data includes chart data, chart title, and chart type. To generate chart titles and types, we initialize selection spaces with GPT-4, which are later refined by human adjustment to align closely with real-world chart contents

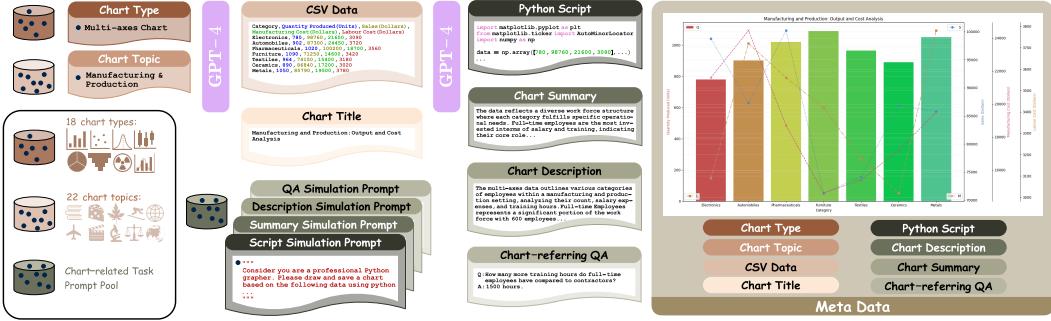


Figure 3: Pipeline of chart data acquisition. For different chart tasks, we design different prompts and data generation processes around 22 chart topics and 18 chart types to enhance the data diversity in the chart domain.

and ensure practical conversion potential to CSV-format data. For chart data generation, GPT-4 is employed to generate the actual data distribution based on the specified length requirements for the given chart type and chart topic.

Data Acquisition: Chart Cognition. The generation of chart cognition data is based on the generated chart perception data. For each chart perception data sample, we design individual instructions with special task templates (refer to Appendix A.2) to generate different cognition task data. Additionally, some chart type-specific instruction examples will be randomly sampled to guide the data generation, which is widely and specially designed for the corresponding chart type and topic. Among these tasks, the generated redrawing code is utilized to further render the chart image, thus constructing the image-label pairs as metadata for the ChartX benchmark, which is further illustrated in Fig. 3 and Appendix A.2.

3.4 Task Evaluation Metrics

SCRM. Given that data in the chart has matrix-like row-column transformation invariance and transpose transformation invariance, Structuring Chart-oriented Representation Metric (SCRM) [34] is employed to evaluate the extracted chart information (*i.e.* SE task), in which the linearized CSV tokens predicted by all models will be transformed to triplet format for performing SCRM evaluation.

GPT-acc & GPT-score. The GPT-acc metric is designed for tasks with unambiguous answers like question-answering, where outputs are evaluated against an exact ground truth using GPT-4. To make a rational evaluation, GPT-acc incorporates a 5% margin of error for numerical responses. Conversely, the GPT-score metric addresses open-ended tasks where responses are subjectively graded. Here, GPT-4 rates summarization, description, and code-redrawing outputs on a **0-5** scale based on manually adjudicated scoring criteria. All the prompts about the manual criteria for each task are described in Appendix B.1, which considers completeness, relevance, accuracy, and creativity of responses.

4 ChartVLM: Chart Vision-Language Model

4.1 Overall Model Design

Here, we introduce ChartVLM, an innovative framework illustrated in Fig. 4. This architecture comprises an instruction adapter, a pixel-level encoder, and a pair of text-level cascaded decoders. The instruction adapter serves as the initial chart task routing module, selecting chart tasks to be executed based on the user’s instructions. For base tasks, such as the prediction of chart title, type, and CSV data, only the base decoder engages. Conversely, the auxiliary decoder will be activated for more intricate generative tasks, building upon the CSV predictions obtained by the base decoder.

The motivations of the cascaded mechanism are: 1) to **augment the model’s interpretability** in cognition tasks through the incorporation of intermediate chart representations, such as CSV data and title, type, and *etc*, and 2) to **improve computational efficiency** by allocating the workload across decoders of varying parameters, wherein the base decoder is significantly smaller than auxiliary decoder.

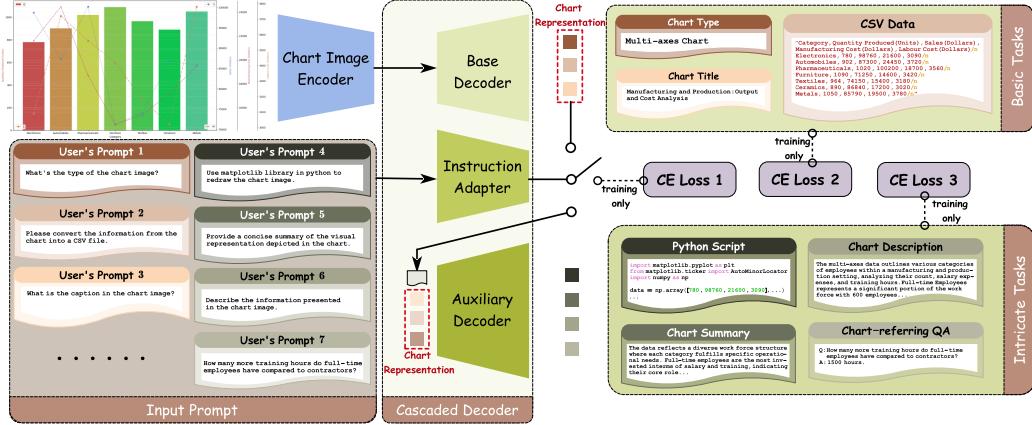


Figure 4: ChartVLM Overview: **a)** To enhance the interpretability of the chart model in cognition tasks (*e.g.*, answer questions based on chart image), ChartVLM first performs the base perception task (*e.g.* structural extraction from the given chart image to a predicted CSV data), and then, finishes other cognition tasks (*e.g.* chart redrawing, description, summary, and QA) based on the extracted structural data. **b)** To choose the task that users expect to perform according to the prompts they use, the instruction adapter is designed to cover a variety of user instructions as illustrated in this figure.

4.2 Instruction Adapter: Instruction Selection

The purposes of designing an instruction adapter are: 1) to meet a broad spectrum of user instructions, and 2) to dynamically select the decoder assigned based on user instructions. The instruction adapter has a simple structure, consisting of only three linear layers, efficiently mapping diverse user instructions to one of seven chart task categories. For training the instruction adapter, we construct a simple dataset using GPT-3.5, containing 7K pairs of user instructions and their task labels. The designed instruction adapter demonstrates flawless performance on the validation subset we constructed, with a 100% accuracy rate.

4.3 Cascaded Decoders Design

The base decoder is developed to extract chart information (mainly CSV data) from a visual chart. If a task is classified as a basic perception task by instruction adapter, the chart at pixel-level will be converted to textual representations output directly (*e.g.* chart title, type, and CSV data) **without the need for auxiliary decoder intervention**. Conversely, when dealing with complicated tasks that require intricate generative processes, the auxiliary decoder will be activated. It leverages both the textual representational outputs from the base decoder and user instructions to execute its sophisticated operations. Once the chart task is determined by the adapter, the cascaded decoders are dynamically and efficiently allocated to meet the varying task requirements.

For basic perception tasks, we fine-tune all the network weights pre-trained from Pix2Struct-base and Pix2Struct-large [16] model, using image-CSV pair data. The fine-tuned encoder and decoder are regarded as chart image encoder and base decoder in ChartVLM. After the fine-tuning stage is completed, the encoder-decoder can effectively transform the chart in image format into a CSV format (*i.e.* chart representation in Fig. 4). For intricate cognition tasks, we utilize LoRA [9] and fine-tune the pre-trained Vicuna-7B and Vicuna-13B as auxiliary decoders using text-text pair data including CSV, QA, summarization, and drawing codes.

Ultimately, two model variants are developed: **ChartVLM-Base-7.3B** (0.3B chart image encoder & base decoder + 7B auxiliary decoder) and **ChartVLM-Large-14.3B** (1.3B chart image encoder & base decoder + 13B auxiliary decoder). All the data we used during fine-tuning stage comes from ChartQA [23], PlotQA [25], Chart2Text [14], and SimChart9K [34]. Besides, the ChartVLM is trained using 32 × NVIDIA Tesla A100.

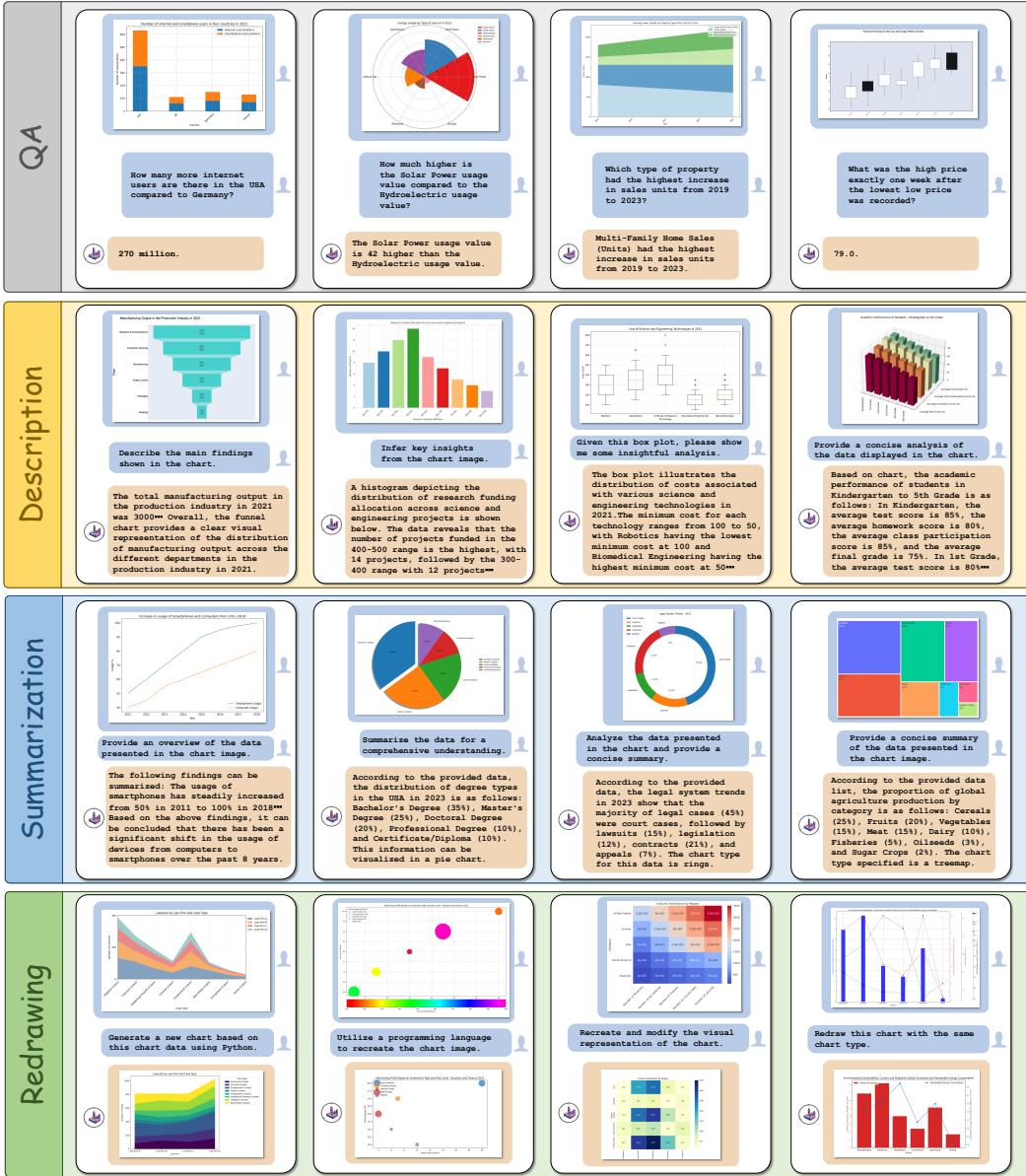


Figure 5: ChartX visualization results of zero-shot chart images using our ChartVLM model. Here we show 4 cognition tasks and please refer to Appendix B.4 for more results of perception tasks.

5 Experiments

5.1 Evaluation Settings

Considering the diversity in different chart types and downstream tasks, the evaluation process of each task should be meticulously designed. Here, we present each necessary post-processing of model predictions on different chart tasks to achieve a more objective evaluation and comparison.

Post-processing of Structural Extraction. For the evaluation of the SE task, considering that the mechanism of SCRM is based on triplet-format matching and some entities may be invisible or irrelative to the visual data in some chart types, the perceived data of several chart types should be post-processed to avoid the prediction errors induced by meaningless perceptions. Specifically, for the percentage-related chart types, *e.g.*, pie chart, ring chart, treemap, funnel chart, *etc.*, the column label of values is usually invisible. Thus, the prediction of this entity for all task evaluations will

Model	#Params	Perception Tasks						Cognition Tasks				
		Structural Extraction			Chart Type EM	Chart Title EM	QA GPT-acc	Chart Desc. GPT-score	Chart Summ. GPT-score	Chart Redraw. GPT-score		
<i>Multi-modal Models</i>												
LLaVA-1.5 [21]	13B	0.04	0.04	0.24	47.05	44.18	17.19	1.48	1.29	0.75		
CogVLM [33]	18B	0.38	0.56	1.01	59.46	94.01	28.30	2.21	1.48	1.38		
QWen-VL [3]	9.6B	4.18	5.86	8.99	69.53	94.62	23.26	1.67	1.45	0.86		
SPHINX-V2 [17]	13B	10.95	23.75	32.07	43.66	92.71	31.16	1.53	1.39	0.96		
GPT-4V [27]	-	<u>20.91</u>	26.00	<u>36.09</u>	70.43	<u>95.22</u>	33.04	<u>3.17</u>	<u>3.12</u>	<u>2.63</u>		
<i>Chart-related Models</i>												
Deplot [18]	1.3B	8.89	19.04	24.08	-	89.84	-	-	-	-		
Matcha [19]	0.3B	0.92	1.10	1.16	5.03	7.90	14.41	-	-	-		
ChartLlama [6]	13B	1.63	2.01	3.19	50.52	40.36	13.80	1.04	1.02	0.94		
StructChart [34]	1.3B	0.46	0.94	1.77	-	-	-	-	-	-		
ChartAst [24]	13B	11.35	22.77	30.18	43.23	92.71	30.99	0.33	1.03	0.82		
<i>Ours</i>												
ChartVLM-B	7.3B	18.49	<u>26.02</u>	32.65	<u>95.67</u>	94.27	<u>36.46</u>	2.05	1.84	1.36		
ChartVLM-L	14.3B	<u>23.18</u>	<u>30.68</u>	<u>38.30</u>	<u>96.82</u>	<u>97.05</u>	<u>40.71</u>	2.17	<u>2.05</u>	<u>1.58</u>		

Table 2: Zero-shot results on both perception and cognition tasks. Comparison with state-of-the-art multi-modal language methods and chart-oriented large models on our proposed ChartX, where Desc. and Summ. denote that chart description and summarization task, respectively. The used evaluation metric for each task is introduced in Sec. 3.4.

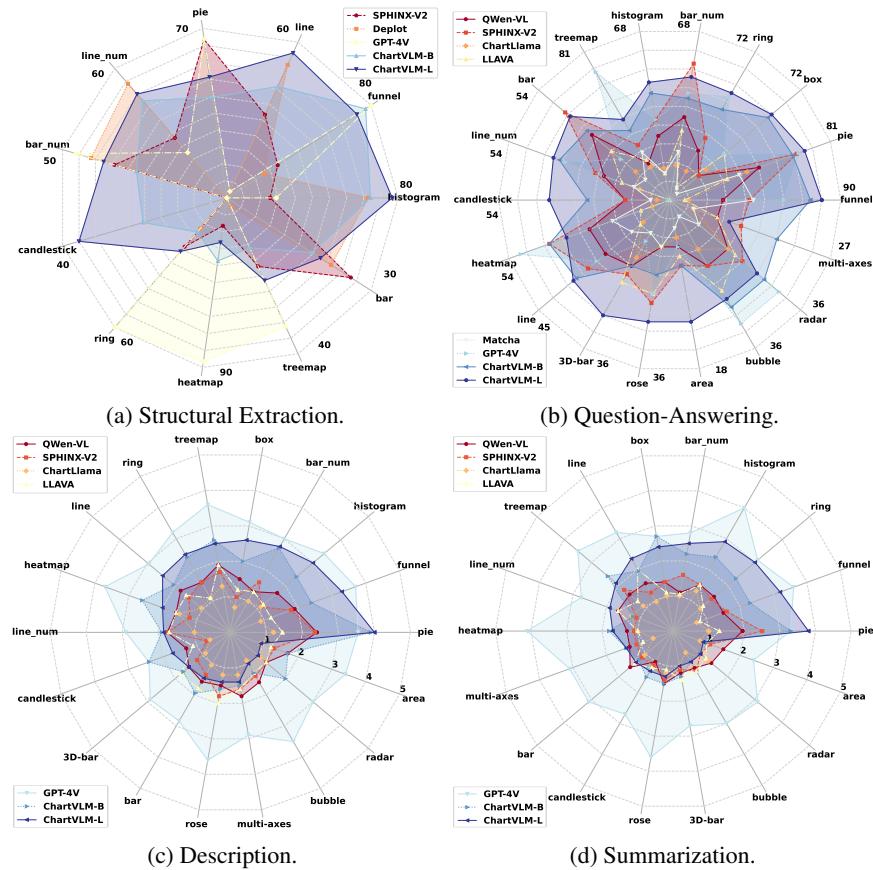


Figure 6: Class-wise results of MLLMs on ChartX.

be manually replaced as ‘value’ or ‘percentage’ to uniform the value representation, namely *entity replacement*.

Prompt Setting for Evaluation. To make a fair comparison between different model performances on the ChartX benchmark, the prompts of different tasks are fine-tuned according to different baseline models to achieve the best performance on each task. The detailed prompt content for each task is illustrated in Fig. A.5 and A.6 of Appendix B.1.

Method	CSV Source	QA Task		Chart Summ.	
		Metric: GPT-acc	Metric: GPT-score		
ChartVLM-B	Golden Table	50.6		3.01	
ChartVLM-B	Predicted	36.5		1.84	
GPT-4V [27]	/	33.0		3.12	

Table 3: Accumulated prediction errors of structural extraction task towards other downstream reasoning tasks such as chart QA and chart summarization.

Model	Perception Tasks				Cognition Tasks				
	SE	Title	Type	Avg.	QA	Summ.	Desc.	Redraw	Avg.
Inference Speed (s):									
LLaVA-1.5 [21]	12.29	0.56	0.41	4.42	0.99	3.48	3.50	11.63	4.90
QWen-VL [3]	4.96	0.93	1.00	2.30	0.38	2.98	2.81	7.43	3.40
SPHINX-V2 [17]	5.53	1.51	1.21	2.75	1.38	3.96	4.09	9.73	4.79
Deplot [18]	3.82	-	-	3.82	-	-	-	-	-
ChartLlama [6]	8.13	0.53	0.42	3.03	0.48	4.13	4.35	13.09	5.51
ChartAst [24]	55.24	3.55	1.37	20.05	3.81	6.06	6.04	34.14	12.51
ChartVLM-B (ours)	2.28	0.39	0.25	0.97	3.41	5.05	4.90	5.85	4.80
ChartVLM-L (ours)	2.87	0.42	0.29	1.19	4.38	6.02	5.98	7.14	5.88

Table 4: Inference speed for both perception and cognition tasks tested on a single Tesla A100 with batch size of 1. The maximum number of tokens generated for each task remains consistent.

5.2 Baseline Models and Main Results

We select two kinds of MLLMs to make a comprehensive comparison. One group of MLLMs is made up of multi-modal large models, where models are trained towards general capability for various vision-language tasks. Here we select five of the most advanced MLLMs for evaluation comparison: LLaVA-1.5 [21], CogVLM [33], QWen-VL [3], SPHINX-V2 [17], and GPT-4V [27]. The other group of MLLMs represents the chart-related large models that are especially fine-tuned on chart-related tasks, including Deplot [18], Matcha [19], StructChart [34], ChartLlama [6], and ChartAssistant [24].

Table 2 shows the main comparison results with various models on ChartX benchmark, from which we can observe the comprehensive evaluation results for each model across various chart tasks and the superiority of ChartVLM. Notably, the proposed ChartVLM-B and ChartVLM-L consistently outperform most models in these tasks (except GPT-4V in the cognition tasks), showcasing the effectiveness of ChartVLMs in understanding information from charts.

Results on Each Chart Type. The class-wise performance of ChartVLMs in seven tasks is shown in Fig. 6. For better visualization, we skip six relatively difficult chart types (rose chart, area chart, 3D-bar chart, bubble chart, multi-axes chart, and radar chart) whose performance is zero-value in all AP metrics for almost all models. The numerical accuracy of these models on seven tasks can be referred to Appendix B.3. From the four subfigures, it can be observed that the type-wise performance of different compared models and our ChartVLM can give a better understanding of different model performances across different chart types.

Comparison with GPT-4V. As shown in Table 2, among all models, GPT-4V [27] is the only model that outperforms our ChartVLM in a few cognition tasks of the ChartX benchmark. This result is reasonable as GPT-4V is currently regarded as the most powerful MLLM for its strong ability to understand and describe information from images, *e.g.*, summarization ability and description ability. However, for the perception tasks, since GPT-4V is a relatively general model, the structural extraction ability is inferior to our ChartVLM, which is specially designed for chart-related tasks. Furthermore, ChartVLM’s stronger ability to extract structural data from a chart image partially leads to a higher accuracy on the chart QA task (40.71%).

5.3 Insightful Analyses

In this part, we conclude five important findings as follows:

- 1) In our cascaded decoder mechanism, increased precision in structural data extraction by the base decoder is positively correlated with improved outcomes in intricate reasoning task performance.

Model	#Params	Structural Extraction		
		AP@Strict	AP@Slight	AP@High
<i>SCRM without Entity Replacement:</i>				
LLaVA-1.5 [21]	13B	0	0	0
QWen-VL [3]	9.6B	1.14	2.40	4.70
SPHINX-V2 [17]	13B	4.70	12.46	18.86
GPT-4V [27]	-	14.35	19.00	27.22
Deplot [18]	1.3B	7.03	16.22	20.76
ChartLlama [6]	13B	1.39	1.68	2.37
ChartAst [24]	13B	5.99	14.93	21.19
ChartVLM-L (ours)	14.3B	22.38	29.22	36.77
<i>SCRM with Entity Replacement:</i>				
LLaVA-1.5 [21]	13B	0.04	0.04	0.24
QWen-VL [3]	9.6B	4.18	5.86	8.99
SPHINX-V2 [17]	13B	10.95	23.75	32.07
GPT-4V [27]	-	20.91	26.00	36.09
Deplot [18]	1.3B	8.89	19.04	24.08
ChartLlama [6]	13B	1.63	2.01	3.19
ChartAst [24]	13B	11.35	22.77	30.18
ChartVLM-L (ours)	14.3B	23.18	30.68	38.30

Table 5: Evaluation results of structural extraction with or without entity replacement.

In Table 2, it is evident that the ChartVLM-L model outperforms ChartVLM-B in SE task, also exhibiting superior performance in intricate cognition tasks, including QA, summarization, etc. Notably, when SE accuracy attains 100% (corresponding to ‘golden table’ in Table 3), our model’s performance on cognition tasks peaks, indicating a direct correlation of performance between basic perception tasks and complicated cognition tasks.

2) *Our ChartVLM exhibits stronger performance in complicated reasoning tasks, owing to our reasoning tasks taking the text representations obtained by the perception task as a conditional input.* Table 2 demonstrates that, despite SPHINX-V2 (32.07%) exhibiting performance close to our ChartVLM (32.65%) in SE task, ChartVLM still demonstrates superior reasoning performance in downstream tasks such as QA tasks (36.46 %). This improvement mainly stems from the novel design of the cascaded decoder mechanism, in which the base decoder enhances complicated reasoning tasks by incorporating the basic perceived results.

3) *Our ChartVLM demonstrates faster inference speed while maintaining a parameter count comparable to the existing open-source models.* Table 4 illustrates a comparative analysis of inference speeds between ChartVLM and other open-source models. Although the inference performance on cognitive tasks is comparable across all models, a significant enhancement in speed is observed for perception tasks in ChartVLM, which is attributed to the exclusive involvement of the lightweight base decoder.

4) *The post-processing implementation of entity replacement significantly alleviates assessment biases.* As shown in Table 5, entity replacement has led to enhanced performance across all baseline models in the SE task, verifying its effectiveness in refining evaluation outcomes.

5) *Current MLLMs exhibit a significant deficit in their capacity to interpret type-specific charts, yielding inferior results in downstream cognitive tasks when benchmarked against GPT-4V.* As evidenced in Tables A.1, A.2, A.3, A.4, and A.5, the existing open-source models demonstrate markedly inferior performance in both the perception and cognition tasks of specialized chart types, such as rose, area, 3D-bar, bubble, multi-axes, and radar charts.

6 Conclusion

In this study, to comprehensively evaluate the chart-related capabilities of MLLMs, we construct ChartX, which is a high-quality, multi-modal, multi-type, multi-topic, and multi-task chart evaluation set. Besides, the ChartVLM framework is developed, which leverages a new cascaded decoder mechanism to boost the interpretability of MLLMs in handling scientific chart data.

References

- [1] Josh Achiam, Steven Adler, Sandhini Agarwal, Lama Ahmad, Ilge Akkaya, Florencia Leoni Aleman, Diogo Almeida, Janko Altenschmidt, Sam Altman, Shyamal Anadkat, et al. Gpt-4 technical report. *arXiv preprint arXiv:2303.08774*, 2023.
- [2] Mubashara Akhtar, Nikesh Subedi, Vivek Gupta, Sahar Tahmasebi, Oana Cocarascu, and Elena Simperl. Chartcheck: An evidence-based fact-checking dataset over real-world chart images. *arXiv preprint arXiv:2311.07453*, 2023.
- [3] Jinze Bai, Shuai Bai, Shusheng Yang, Shijie Wang, Sinan Tan, Peng Wang, Junyang Lin, Chang Zhou, and Jingren Zhou. Qwen-vl: A frontier large vision-language model with versatile abilities. *arXiv preprint arXiv:2308.12966*, 2023.
- [4] Tom Brown, Benjamin Mann, Nick Ryder, Melanie Subbiah, Jared D Kaplan, Prafulla Dhariwal, Arvind Neelakantan, Pranav Shyam, Girish Sastry, Amanda Askell, et al. Language models are few-shot learners. *Advances in neural information processing systems*, 33:1877–1901, 2020.
- [5] Sébastien Bubeck, Varun Chandrasekaran, Ronen Eldan, Johannes Gehrke, Eric Horvitz, Ece Kamar, Peter Lee, Yin Tat Lee, Yuanzhi Li, Scott Lundberg, et al. Sparks of artificial general intelligence: Early experiments with gpt-4. *arXiv preprint arXiv:2303.12712*, 2023.
- [6] Yucheng Han, Chi Zhang, Xin Chen, Xu Yang, Zhibin Wang, Gang Yu, Bin Fu, and Hanwang Zhang. Chartllama: A multimodal llm for chart understanding and generation. *arXiv preprint arXiv:2311.16483*, 2023.
- [7] Muhammad Yusuf Hassan, Mayank Singh, et al. Lineex: Data extraction from scientific line charts. In *Proceedings of the IEEE/CVF Winter Conference on Applications of Computer Vision*, pages 6213–6221, 2023.
- [8] Xinyi He, Mengyu Zhou, Xinrun Xu, Xiaojun Ma, Rui Ding, Lun Du, Yan Gao, Ran Jia, Xu Chen, Shi Han, et al. Text2analysis: A benchmark of table question answering with advanced data analysis and unclear queries. *arXiv preprint arXiv:2312.13671*, 2023.
- [9] Edward J Hu, Yelong Shen, Phillip Wallis, Zeyuan Allen-Zhu, Yuanzhi Li, Shean Wang, Lu Wang, and Weizhu Chen. Lora: Low-rank adaptation of large language models. *arXiv preprint arXiv:2106.09685*, 2021.
- [10] Kung-Hsiang Huang, Mingyang Zhou, Hou Pong Chan, Yi R Fung, Zhenhailong Wang, Lingyu Zhang, Shih-Fu Chang, and Heng Ji. Do lvlms understand charts? analyzing and correcting factual errors in chart captioning. *arXiv preprint arXiv:2312.10160*, 2023.
- [11] Siyuan Huang, Zhengkai Jiang, Hao Dong, Yu Qiao, Peng Gao, and Hongsheng Li. Instruct2act: Mapping multi-modality instructions to robotic actions with large language model. *arXiv preprint arXiv:2305.11176*, 2023.
- [12] Albert Q Jiang, Sean Welleck, Jin Peng Zhou, Wenda Li, Jiacheng Liu, Mateja Jamnik, Timothée Lacroix, Yuhuai Wu, and Guillaume Lample. Draft, sketch, and prove: Guiding formal theorem provers with informal proofs. *arXiv preprint arXiv:2210.12283*, 2022.
- [13] Kushal Kafle, Brian Price, Scott Cohen, and Christopher Kanan. Dvqa: Understanding data visualizations via question answering. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 5648–5656, 2018.
- [14] Shankar Kanthara, Rixie Tiffany Ko Leong, Xiang Lin, Ahmed Masry, Megh Thakkar, Enamul Hoque, and Shafiq R. Joty. Chart-to-text: A large-scale benchmark for chart summarization. In *Annual Meeting of the Association for Computational Linguistics*, 2022.
- [15] Shankar Kantharaj, Xuan Long Do, Rixie Tiffany Ko Leong, Jia Qing Tan, Enamul Hoque, and Shafiq Joty. Opencqa: Open-ended question answering with charts. *arXiv preprint arXiv:2210.06628*, 2022.
- [16] Kenton Lee, Mandar Joshi, Iulia Raluca Turc, Hexiang Hu, Fangyu Liu, Julian Martin Eisenschlos, Urvashi Khandelwal, Peter Shaw, Ming-Wei Chang, and Kristina Toutanova. Pix2struct: Screenshot parsing as pretraining for visual language understanding. In *International Conference on Machine Learning*, pages 18893–18912. PMLR, 2023.
- [17] Ziyi Lin, Chris Liu, Renrui Zhang, Peng Gao, Longtian Qiu, Han Xiao, Han Qiu, Chen Lin, Wenqi Shao, Keqin Chen, et al. Sphinx: The joint mixing of weights, tasks, and visual embeddings for multi-modal large language models. *arXiv preprint arXiv:2311.07575*, 2023.

- [18] Fangyu Liu, Julian Martin Eisenschlos, Francesco Piccinno, Syrine Krichene, Chenxi Pang, Kenton Lee, Mandar Joshi, Wenhui Chen, Nigel Collier, and Yasemin Altun. Deplot: One-shot visual language reasoning by plot-to-table translation. *arXiv preprint arXiv:2212.10505*, 2022.
- [19] Fangyu Liu, Francesco Piccinno, Syrine Krichene, Chenxi Pang, Kenton Lee, Mandar Joshi, Yasemin Altun, Nigel Collier, and Julian Martin Eisenschlos. Matcha: Enhancing visual language pretraining with math reasoning and chart derendering. *arXiv preprint arXiv:2212.09662*, 2022.
- [20] Fuxiao Liu, Xiaoyang Wang, Wenlin Yao, Jianshu Chen, Kaiqiang Song, Sangwoo Cho, Yaser Yacoob, and Dong Yu. Mmc: Advancing multimodal chart understanding with large-scale instruction tuning. *arXiv preprint arXiv:2311.10774*, 2023.
- [21] Haotian Liu, Chunyuan Li, Yuheng Li, and Yong Jae Lee. Improved baselines with visual instruction tuning. *arXiv preprint arXiv:2310.03744*, 2023.
- [22] Junyu Luo, Zekun Li, Jinpeng Wang, and Chin-Yew Lin. Chartocr: Data extraction from charts images via a deep hybrid framework. In *Proceedings of the IEEE/CVF winter conference on applications of computer vision*, pages 1917–1925, 2021.
- [23] Ahmed Masry, Do Xuan Long, Jia Qing Tan, Shafiq Joty, and Enamul Hoque. Chartqa: A benchmark for question answering about charts with visual and logical reasoning. *arXiv preprint arXiv:2203.10244*, 2022.
- [24] Fanqing Meng, Wenqi Shao, Quanfeng Lu, Peng Gao, Kaipeng Zhang, Yu Qiao, and Ping Luo. Chartistassistant: A universal chart multimodal language model via chart-to-table pre-training and multitask instruction tuning. *arXiv preprint arXiv:2401.02384*, 2024.
- [25] Nitesh Methani, Pritha Ganguly, Mitesh M Khapra, and Pratyush Kumar. Plotqa: Reasoning over scientific plots. In *Proceedings of the IEEE/CVF Winter Conference on Applications of Computer Vision*, pages 1527–1536, 2020.
- [26] Jason Obeid and Enamul Hoque. Chart-to-text: Generating natural language descriptions for charts by adapting the transformer model. *arXiv preprint arXiv:2010.09142*, 2020.
- [27] OpenAI. Gpt-4v(ision) system card. <https://openai.com/contributions/gpt-4v>, 2023.
- [28] Long Ouyang, Jeffrey Wu, Xu Jiang, Diogo Almeida, Carroll Wainwright, Pamela Mishkin, Chong Zhang, Sandhini Agarwal, Katarina Slama, Alex Ray, et al. Training language models to follow instructions with human feedback. *Advances in Neural Information Processing Systems*, 35:27730–27744, 2022.
- [29] Chinmayee Rane, Seshasayee Mahadevan Subramanya, Devi Sandeep Endluri, Jian Wu, and C Lee Giles. Chartreader: Automatic parsing of bar-plots. In *2021 IEEE 22nd International Conference on Information Reuse and Integration for Data Science (IRI)*, pages 318–325. IEEE, 2021.
- [30] David Saxton, Edward Grefenstette, Felix Hill, and Pushmeet Kohli. Analysing mathematical reasoning abilities of neural models. *arXiv preprint arXiv:1904.01557*, 2019.
- [31] Yuan Tian, Weiwei Cui, Dazhen Deng, Xinjing Yi, Yurun Yang, Haidong Zhang, and Yingcai Wu. Chartgpt: Leveraging llms to generate charts from abstract natural language. *arXiv preprint arXiv:2311.01920*, 2023.
- [32] Trieu H Trinh, Yuhuai Wu, Quoc V Le, He He, and Thang Luong. Solving olympiad geometry without human demonstrations. *Nature*, 625(7995):476–482, 2024.
- [33] Weihan Wang, Qingsong Lv, Wenmeng Yu, Wenyi Hong, Ji Qi, Yan Wang, Junhui Ji, Zhuoyi Yang, Lei Zhao, Xixuan Song, et al. Cogvilm: Visual expert for pretrained language models. *arXiv preprint arXiv:2311.03079*, 2023.
- [34] Renqiu Xia, Bo Zhang, Haoyang Peng, Ning Liao, Peng Ye, Botian Shi, Junchi Yan, and Yu Qiao. Structchart: Perception, structuring, reasoning for visual chart understanding. *arXiv preprint arXiv:2309.11268*, 2023.
- [35] Zhengzhuo Xu, Sinan Du, Yiyan Qi, Chengjin Xu, Chun Yuan, and Jian Guo. Chartbench: A benchmark for complex visual reasoning in charts. *arXiv preprint arXiv:2312.15915*, 2023.
- [36] Kaiyu Yang, Aidan M Swope, Alex Gu, Rahul Chalamala, Peiyang Song, Shixing Yu, Saad Godil, Ryan Prenger, and Anima Anandkumar. Leandojo: Theorem proving with retrieval-augmented language models. *arXiv preprint arXiv:2306.15626*, 2023.
- [37] Zhengyuan Yang, Linjie Li, Kevin Lin, Jianfeng Wang, Chung-Ching Lin, Zicheng Liu, and Lijuan Wang. The dawn of lmms: Preliminary explorations with gpt-4v (ision). *arXiv preprint arXiv:2309.17421*, 9(1), 2023.

- [38] Liangyu Zha, Junlin Zhou, Liyao Li, Rui Wang, Qingyi Huang, Saisai Yang, Jing Yuan, Changbao Su, Xiang Li, Aofeng Su, et al. Tablegpt: Towards unifying tables, nature language and commands into one gpt. *arXiv preprint arXiv:2307.08674*, 2023.

A Details of ChartX Evaluation Set

We present the zoom-in characteristics of the ChartX evaluation set by detailing the data distribution and its generation pipeline.

A.1 Introduction of Chart Topics

The categories of chart topics have been concisely displayed in Fig. 1 of the main text. Here a more detailed distribution is introduced for a clear visualization. As shown in Fig. A.1, there are a total of 22 chart topics, generally covering the fields of commerce, industry, lifestyle, society, and culture. Each topic is evenly distributed in ChartX, demonstrating its comprehensiveness.

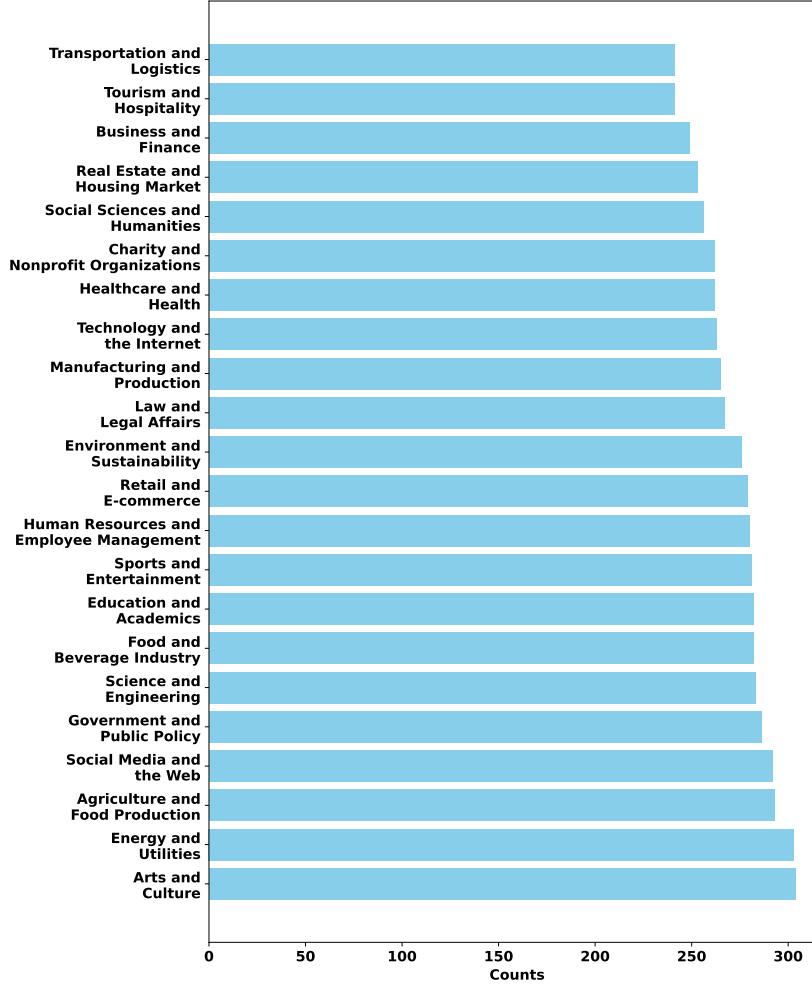


Figure A.1: The distribution of fine-grained chart topics.

A.2 Overall of Data Generation Pipeline

We first describe the overall data generation pipeline, including perception data and cognition data. Then, the prompt templates for different data generation are provided.

Data Generation Pipeline. As shown in Fig. 3, during the first stage, we prepare a chart type pool and a chart topic pool in which the candidates are pre-selected based on GPT-4, where those chart types of an explicit connection or mapping with CSV-format data are selected as candidates of the chart type pool. After achieving such two pools, we iteratively and randomly sample the candidates from two pools and fill them into the pre-designed prompt template to generate CSV data associated

with the chart title. Once the pair of CSV data and the corresponding chart title are generated, they are both filled into various task-specific and type-specific prompt templates to generate cognition task samples.

Prompt Design for Overall Data Generation. We provide a general prompt template for overall data generation, including perception data and cognition data in Fig. A.2. For perception data generation, we impose constraints on the magnitude and length of the data to make most data visible and recognizable in the chart image. For cognition data generation, we impose task-specific guidance to generate the corresponding ground-truth labels for each task. The diversity in different tasks is achieved through designing type-specific prompts. Here we provide two examples to illustrate type-specific prompts (marked red in Fig. A.2) in overall data generation. Fig. A.3 shows the detailed type-specific prompts to generate code data and QA samples of 3D-bar charts, rose charts, box plots and candlesticks.

A.3 Examples of ChartX

Fig. A.4 provides more examples of metadata in the generated dataset, including the chart type, title, topic, CSV data, QA pairs, summarization, description, and the redrawing code. It can be observed that:

- (1) The generated data are closely related to the assigned chart types and topics.
- (2) The generated QA pairs are closely related to the characteristics of the given chart types and topics, increasing the overall diversity.
- (3) The generated summary and description concisely and accurately describe the content of the assigned chart data.

B Experimental Details

We provide detailed experimental information in this section, including the evaluation criteria of all tasks, the quantitative results for each chart type, and more visualizations of prediction results.

B.1 Evaluation Settings

Prompt Design for GPT-acc and GPT-score. We adopt GPT-acc as the evaluation metric for the QA task, and GPT-score for the description, summarization, and redrawing tasks, respectively. The complete prompts and manual criteria are concluded in Fig. A.5 and A.6.

Employed Threshold of SCRM. According to the definition of SCRM metric proposed in StructChart [34], three different levels of tolerance ($\text{tol} := \{\text{strict}, \text{slight}, \text{high}\}$) are set for fine-grained evaluation of SE task. Considering the different perception difficulties of different types of charts, we divide all 18 types of charts into two difficulty levels: normal and difficult, and set different thresholds for tolerance respectively.

For normal charts, including *bar chart*, *line chart*, *pie chart*, *bar chart with number*, *line chart with number*, *ring chart*, *heatmap*, *box plot*, *candlestick*, *funnel chart*, *histogram*, and *treemap*:

$$\begin{aligned} \text{strict} &:= \{J_{thr}|_{\text{tol}} = 0 \wedge e_{thr}|_{\text{tol}} = 0\}, \\ \text{slight} &:= \{J_{thr}|_{\text{tol}} = 2 \wedge e_{thr}|_{\text{tol}} = 0.05\}, \\ \text{high} &:= \{J_{thr}|_{\text{tol}} = 5 \wedge e_{thr}|_{\text{tol}} = 0.1\}, \end{aligned} \quad (\text{A.1})$$

For difficult charts, including *rose chart*, *area chart*, *3D-Bar chart*, *bubble chart*, *multi-axes chart*, and *radar chart*:

$$\begin{aligned} \text{strict} &:= \{J_{thr}|_{\text{tol}} = 0 \wedge e_{thr}|_{\text{tol}} = 0.1\}, \\ \text{slight} &:= \{J_{thr}|_{\text{tol}} = 2 \wedge e_{thr}|_{\text{tol}} = 0.3\}, \\ \text{high} &:= \{J_{thr}|_{\text{tol}} = 5 \wedge e_{thr}|_{\text{tol}} = 0.5\}, \end{aligned} \quad (\text{A.2})$$

where $J_{thr}|_{\text{tol}}$ indicates the edit distance threshold between prediction and GT string, $e_{thr}|_{\text{tol}}$ refers to the relative error threshold between prediction numeric value and GT value.



Perception Data Generation Template

Refer to the following topic, generate the csv format data. Generate a title based on the topic and data, place it after the marker '[title]'. Information containing in the data can be expanded and adapted as appropriate to fit the type of [the selected chart type]. The chart theme is [the selected theme]. The imitation is as irrelevant as possible to the original text. [Data value specification]. [Data length specification]. The difference of each data point should not be too large. Each row of the data represents the different aspects of one category.



Code Generation Template

Consider you are a professional Python grapher.
 Please draw and save a chart based on the following data using python, and images must be clear and intuitive. The code should have no extra indent.
 Transform the given data into three variables: `data_labels`, `data`, `line_labels`. `Data_labels` represents the labels of each column except the first column. `Line_labels` represents the labels of each row except the first row. `Data` represent the numerical array in the data.
 Plot the data with the type of [the selected chart type].
`[The base setting of plotting the selected chart type.]`
`[The specific setting of plotting code to increase diversity.]`
 The image must be saved as `[path_to_save].png`.
 Clear the current image state at the end of the code.
 Automatically resize the image by `tight_layout()` before `savefig()`.
 The title of the figure should be [the generated chart title].
 If the string in the picture is too long, find a way for all characters to show and not be overwritten and stacked on top of each other.
 Do not have extra leading words at the beginning and end of the generated code, such as "python code, python, ''", etc. Check the generated code to make sure it doesn't report errors, do not include undefined functions.
`Data: [the generated CSV data]`



QA Generation Template

`[type_specific_examples]`

According to the input csv data with the given title and chart type, design one question-answer pair with medium difficulty that can be answered directly through data.
 Each answer should not contain any hints, explanations or notes, etc.
`Data: [the generated CSV data]`
`Title: [the generated title]`
`Type: [the selected chart type]`



Description Generation Template

Generate a descriptive text of 100 words or less based on the CSV data, title, and chart type.
 Describe the data objectively, without any summarization or findings.
`Data: [the generated CSV data]`
`Title: [the generated title]`
`Type: [the selected chart type]`



Summarization Generation Template

Generate a summarization text of 100 words or less based on the CSV data, title, and chart type. Do not describe the data objectively, give some summarization and findings.
`Data: [the generated CSV data]`
`Title: [the generated title]`
`Type: [the selected chart type]`

Figure A.2: Prompts designed for overall data generation, including perception data and cognition data. The content marked red refers to the type-specific prompt, which will be illustrated in Fig. A.3.

B.2 Maximum number of generate token settings

To fairly compare the performance of models on various tasks, we unify the maximum number of generate token (`max_token`) of different models on the same task. The details of `max_token` can be concluded: 1) 1280 for SE, 2) 100 for title, 3) 20 for type, 4) 100 for QA, 5) 512 for description and summarization, and 6) 1024 for redrawing code. This setting is still maintained for inference speed testing

 **Code Generation Template** 

[Basic setting of 3D-bar chart]:
 Transform the given data into three variables: `y_values`, `data`, `x_values`. `y_values` represents the metric list of each column except the first column. `x_values` represents the category list of each row except the first row. Data represent the numerical ndarray in the data, where each row corresponds to a category and each column corresponds to a metric.
 Plot the data with the type of 3D-bar chart. use a 3D projection for the subplot.
 Iterate over `y_values` to plot each column of data. For the plotting of each column in data, use `np.arange(len(x_labels))` and `[i]*len(x_labels)` to represent the X, Y coordinates for each group of data to avoid overlapping of different data groups, and use `bar3d` to draw a set of bars, in which ensure that each group of bars is correctly aligned on x-axis.

[Specific setting of 3D-bar chart]:
 Set the dimensions of the bars (width, depth, colors, alpha, etc) differently on x-dimension or y-dimension to ensure they are distinct and non-overlapping, providing clear visualization. Rotate the X-axis labels for better readability.

[Specific setting of 3D-bar chart]
 Drawing techniques such as background grids can be used. Viewing angles can be adjusted to make all data bars readable. Drawing as much variations as possible to increase diversity.

 **Code Generation Template** 

[Basic setting of rose chart]:
 Plot the data with the type of rose chart. Modify the axes to use polar coordinates with '`polar=True`' or '`projection='polar'`'.
 There should be multiple sectors in the graph, each representing a different category, assign a different color to each sector, and add a legend next to the chart that clearly labels the category each sector represents, ensuring that the legend does not obscure any part of the chart. All sectors should cover the entire circumference evenly.
 Different sectors represent different categories with the same angle, whose radius is proportional to the corresponding value, and the angles of these sectors must add up to 360 degrees, i.e., use "`sector_angle = (2 * np.pi) / num_categories`" to calculate the sector angle and draw sectors corresponding to different categories by making the width parameter in "`ax.bar`" `sector_angle`".

[Specific setting of rose chart]:
 Drawing techniques such as background grids can be used...
 Drawing as much variations as possible to increase diversity. Hyper-parameters like rotation direction in the plotting functions can be tuned to achieve more diversity.

 **QA Generation Template** 

[Type-specific example for box plot]:

```
input: <csv> Product \t Min \t Q1 \t Median \t Q3 \t Max \t Outlier \n Whole Grain Bread \t 3 \t 3.5 \t 4 \t 4.5 \t 5 \t [] \n Red Wine \t 15 \t 20 \t 25 \t 30 \t 35 \t [45,50] \n White Meat \t 5 \t 7 \t 9 \t 11 \t 15 \t [] <title> Price Distribution of Selected Food and Beverage Products (2022)

output: Q: Which product has the largest range of price fluctuation?
A: Red Wine.
```

 **QA Generation Template** 

[Type-specific example for candlestick]:

```
input: <csv> <csv> Date \t Opening Price ($) \t Closing Price ($) \t High Price ($) \t Low Price ($) \n 2022-03-01 \t 120 \t 123 \t 130 \t 118 \n 2022-03-02 \t 125 \t 128 \t 135 \t 122 \n 2022-03-03 \t 130 \t 135 \t 140 \t 128 \n 2022-03-04 \t 135 \t 138 \t 140 \t 125 \n 2022-03-05 \t 140 \t 145 \t 150 \t 138 \n 2022-03-06 \t 145 \t 150 \t 155 \t 143 <title> March 2022 Daily Stock Prices in Technology Sector

output: Q: Which day has the largest price fluctuation that the difference between high price and low price is the largest?
A: 2022-03-02.
```

Figure A.3: Examples of type-specific prompt design for 3D-bar chart, rose chart, box plot and candlesticks.

B.3 Quantitative Results for Each Chart Type

We have presented part of the class-wise performance in Fig. 6 of the main text. Here, more comprehensive testing results of various models on all tasks are listed in Tables A.1, A.2, A.3, A.4, and A.5. Specifically, we compare recent multi-modal language models and chart-related models with ChartVLMs on QA, SE, description, summarization and redrawing tasks. The results show a

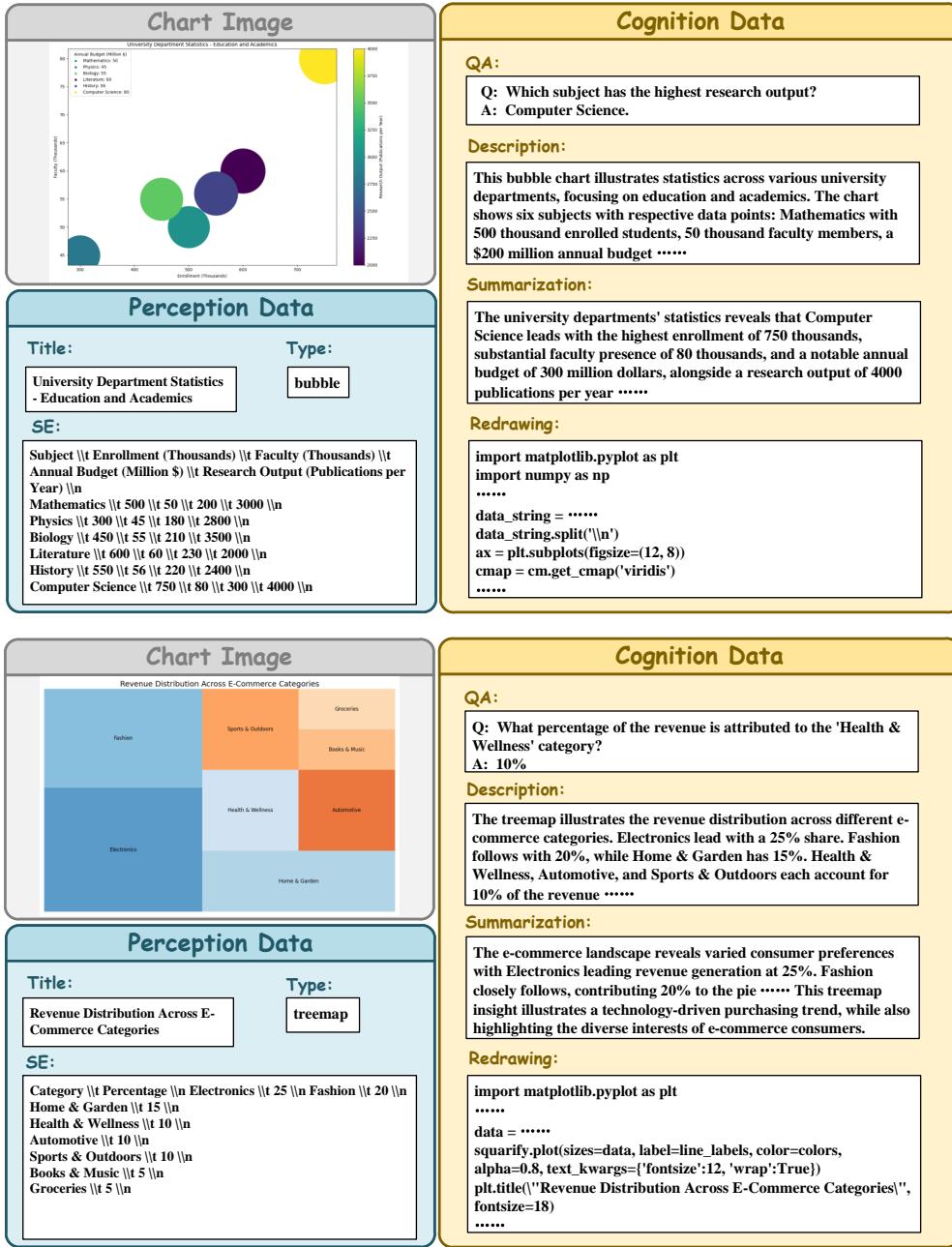


Figure A.4: Two examples of metadata in ChartX, including the chart type, title, topic, CSV data, QA pairs, summarization, description, and the redrawing code.

comprehensive superiority of ChartVLMs to the existing models in most chart types and tasks. It should be noted that except for GPT-4V, whose scores of summary and description are higher than the average score, the downstream reasoning tasks seem quite tough for all models. This shed light on the common challenge in learning chart-related language models: how to fully learn multiple tasks in a single model without sacrificing the generalization ability to a new chart domain.

B.4 Visualization Results of Perception Tasks

We provide four visualization perception results for different types of charts in Fig. A.7, including funnel chart, histogram, radar chart and line chart. The results demonstrate that our ChartVLM



GPT-score for Summarization Task

Criterion:

You're an expert evaluating a model's summarization of a chart, based on its alignment with the ground truth and raw data. Score the model from 0 to 5 based on these criteria:

- 0 points: The summary is irrelevant or shows no understanding of the original text, failing to address the core content or theme.
- 1 point: While referencing the original text, the summary contains predominantly incorrect details or interpretations, showing minimal understanding and significant inaccuracies.
- 2 points: The summary captures some correct details, indicating a basic understanding. However, it misses key elements or includes major inaccuracies, leading to a flawed interpretation of the text.
- 3 points: Most details in the summary are accurate, reflecting a good understanding of the original text. Minor errors or omissions are present but don't significantly impact the overall accuracy or comprehension.
- 4 points: The summary accurately represents all main ideas and important details of the original text. It shows a very good understanding, with minor room for improvement in clarity, conciseness, or structure.
- 5 points: This represents a comprehensive and accurate summary, perfectly encapsulating all essential aspects of the original text. It demonstrates excellent understanding, is error-free, clear, concise, well-structured, and serves as an excellent standalone representation of the original content.

Score the model's summarization on this scale, providing a single value without providing any reasons.

Input:

```
f```
data: {csv_gt} <title> {title} <type> {chart_type}\nsummarization: {summ}
```
```



## GPT-score for Description Task

### Criterion:

You're an expert evaluating a model's description of a chart, based on its alignment with the ground truth and raw data. Score the model from 0 to 5 based on these criteria:

- 0 points: Description irrelevant or shows no understanding of the chart or data.
- 1 point: Refers to the chart but with largely incorrect details; minimal understanding.
- 2 points: Some correct details, but key elements are wrong or missing; basic understanding with significant errors.
- 3 points: Most details are correct; good understanding but with minor errors/omissions.
- 4 points: All details are correct; very good understanding, minor improvements possible.
- 5 points: Comprehensive, accurate description; excellent understanding with no errors; clear and detailed, perfect as a standalone explanation.

Score the model's description on this scale, providing a single value without providing any reasons.

### Input:

```
f```
data: {csv_gt} <title> {title} <type> {chart_type}\ndescription: {des}
```
```

Figure A.5: Detailed prompts in GPT-score metric for summarization and description tasks.

performs well on chart title and the chart-type prediction task. Even if the SE result of the radar chart is slightly wrong, ChartVLM still has strong SE performance on the funnel chart, histogram, and line chart.



GPT-score for Redrawing Task

Criterion:

You're an expert evaluating a redrawing code of a chart, based on its alignment with the ground truth and raw data. Score the code from 0 to 5 based on these criteria:

- 0 points: Completely Irrelevant or Non-functional Code. Demonstrates no understanding of the chart structure or data. Code is inexecutable or produces a completely unrelated chart.
- 1 point: Attempted Redraw with Major Discrepancies. Partial understanding of basic chart structure or data. Generated chart has very little in common with the original.
- 2 points: Partially Correct Code with Key Errors or Omissions. Basic understanding of chart structure or data but with significant errors. Chart somewhat resembles the original but key inaccuracies are evident.
- 3 points: Mostly Accurate; Good Understanding with Minor Errors/Omissions. Accurately reflects most of the chart's structure and data. Generated chart is similar to the original but has a few minor errors.
- 4 points: Highly Accurate; Very Good Understanding with Minor Room for Improvement. Accurately presents the chart's structure and data in full. Generated chart is very close to the original, with negligible differences.
- 5 points: Comprehensive, Accurate Code; Excellent Understanding, No Errors. Perfectly replicates all details and data of the chart. Generated chart is indistinguishable from the original, flawless.

Score the redrawing code on this scale, providing a single value without providing any reasons.

Input:

```
f```
data: {csv_gt} <title> {title} <type> {chart_type}\n
redrawing code: {redrawing_code}
```
```



## GPT-acc for QA Task

### Examples:

```
{
 "query": "<question> What was the incremental increase in revenue from 2020 to 2021?\n <groundtruth answer> 5 million \$ <answer> 20\n</s>",
 "answer": "False"
},
{
 "query": "<question> What percentage of government spending was allocated to infrastructure\n in 2020? <groundtruth answer> 10% <answer> 14-4=10\n</s>",
 "answer": "True"
}
```

### Instruction:

Given multiple QA pairs and the corresponding predictions, evaluate the correctness of predictions. The output should be only "True" or "False". Note that if the GT answer is a numeric value with/without the unit, impose 5% error tolerance to the answer

### Input:

```
f```
<question> {question} <groundtruth answer> {answer_gt} <answer> {answer_pred}
```
```

Figure A.6: Detailed prompts in GPT-score metric for redrawing task and GPT-acc metric for QA task.

Models	Tasks	General Chart Types						Fine-grained Chart Types										Avg.		
		bar	bar,unrm	line	line,unrm	pie	ring	box	hist	treemap	rose	area	3D-bar	bubbles	multi	radar	heatmap	funnel		
SPHINX-V2	bar	■2.50	■20.10	■72.00	■9.90	■35.10	■9.00	■0.00	■2.00	■17.60	■15.40	■0.00	■0.00	■0.00	■0.00	■0.00	■9.81	■26.00	■0.95	
	bar,unrm	■17.40	■34.20	■36.40	■27.80	■65.40	■22.60	■0.00	■20.20	■17.60	■51.00	■0.00	■2.60	■0.00	■0.00	■8.00	■14.81	■28.20	■0.00	
	line	■39.40	■46.00	■47.90	■39.70	■76.20	■27.80	■0.80	■25.60	■18.40	■71.40	■1.40	■1.60	■0.00	■0.00	■16.00	■18.46	■34.20	■0.00	
Deplot	line	■2.20	■33.70	■16.00	■22.30	■0.00	■14.20	■0.00	■20.20	■2.40	■0.00	■0.00	■0.00	■0.00	■0.00	■0.00	■0.00	■19.60	■0.00	
	line,unrm	■21.70	■41.30	■51.20	■52.90	■0.00	■14.20	■0.00	■66.00	■2.40	■0.20	■0.20	■0.00	■0.00	■0.00	■0.20	■0.40	■0.00	■20.80	■0.00
	pie	■42.10	■48.70	■60.10	■61.20	■0.00	■14.60	■0.00	■82.20	■3.00	■0.00	■0.00	■0.00	■0.00	■0.00	■0.40	■1.00	■0.00	■23.60	■0.00
ChartAst	SE	■7.80	■22.10	■8.20	■11.50	■44.30	■14.40	■0.00	■85.40	■13.60	■24.00	■0.00	■0.00	■1.40	■0.00	■0.00	■13.65	■20.20	■0.00	
		■21.70	■33.80	■40.10	■35.20	■51.00	■14.80	■0.00	■24.80	■14.60	■25.20	■0.00	■3.80	■1.80	■0.00	■26.00	■20.00	■11.20	■0.00	
		■38.40	■44.60	■48.00	■41.70	■63.70	■14.80	■0.00	■03.80	■15.80	■10.60	■0.00	■7.00	■1.20	■0.00	■38.00	■24.04	■15.00	■0.00	
GPT-4V	area	■0.00	■25.00	■0.00	■15.50	■65.50	■60.00	■0.00	■20.00	■33.00	■0.00	■0.00	■0.00	■0.00	■0.00	■0.00	■76.00	■80.00	■0.00	
	area,unrm	■0.00	■46.00	■2.50	■21.00	■65.50	■60.00	■0.00	■23.00	■33.00	■10.00	■0.00	■12.00	■3.00	■0.00	■20.00	■87.00	■80.00	■0.00	
	3D-bar	■0.00	■53.00	■24.50	■41.00	■67.00	■50.00	■0.00	■89.00	■1.00	■49.00	■18.00	■0.00	■0.00	■20.00	■22.00	■0.00	■62.00	■88.00	■0.00
ChartVLM-B	3D-bar	■0.00	■20.40	■26.30	■29.10	■40.70	■15.80	■0.00	■38.00	■12.80	■0.00	■0.00	■0.00	■0.00	■0.00	■0.00	■28.08	■76.00	■0.00	
	area	■17.70	■27.50	■42.90	■45.00	■41.50	■15.80	■1.60	■67.00	■12.80	■5.80	■0.00	■2.20	■0.80	■0.00	■12.20	■33.46	■77.40	■20.40	
	area,unrm	■21.20	■33.00	■51.90	■54.80	■43.20	■20.60	■13.20	■75.00	■15.20	■22.40	■9.60	■1.60	■1.20	■18.40	■35.77	■77.48	■47.00	■2.65	
ChartVLM-L	area	■16.30	■34.00	■37.60	■34.70	■49.90	■24.80	■0.00	■15.80	■21.20	■0.00	■0.00	■0.00	■0.00	■0.00	■0.00	■14.40	■23.65	■72.20	■0.00
	area,unrm	■19.50	■37.50	■55.80	■48.10	■49.90	■24.80	■0.40	■77.20	■21.20	■3.00	■1.80	■2.40	■2.00	■0.00	■19.60	■23.65	■72.20	■30.68	
	3D-bar	■27.90	■42.00	■60.40	■51.50	■51.80	■28.40	■19.80	■72.70	■21.80	■27.60	■9.80	■8.00	■0.00	■10.60	■32.20	■25.19	■73.20	■69.20	

Table A.1: **Class-wise mean precision for Structural Extraction (SE) task evaluated using SCRM [34]**. For some hard fine-grained classes such as bubble chart, radar chart, etc, we use the relatively high tolerance for evaluating the SCRM results as introduced in Sec. B.1. Note that the color blocks represent the tolerance level we set in SCRM, where ■, □, ▨ indicate strict, slight, high tolerance, respectively.

Models	Tasks	General Chart Types						Fine-grained Chart Types										Avg.		
		bar	bar,num	line	line,num	pie	ring	box	hist	treemap	rose	area	area	3D-bar	bubble	multi	radar	heatmap	funnel	
Qwen-VL SPHINX-V2 ChartLlama Qwen-40B LLaVA-1.5 Matcha GPT-4V CharVLM-B CharVLM-L	QA	33.00	31.00	22.00	22.00	45.00	24.00	16.00	24.00	20.00	10.00	10.00	16.00	16.00	8.00	16.00	26.92	28.00	14.00	23.26
		35.00	51.00	31.00	25.00	64.00	30.00	16.00	30.00	30.00	22.00	14.00	18.00	16.00	12.00	20.00	40.38	42.00	14.00	31.16
		14.00	13.00	9.00	10.00	39.00	14.00	20.00	12.00	18.00	10.00	8.00	14.00	12.00	4.00	16.00	5.74	10.00	4.00	13.80
		24.00	25.00	29.00	29.00	38.00	24.00	20.00	38.00	28.00	24.00	16.00	14.00	20.00	20.00	22.00	40.00	44.00	14.00	30.00
		24.00	26.00	10.00	16.00	20.00	6.00	30.00	10.00	22.00	10.00	12.00	8.00	18.00	9.00	6.00	8.00	17.18	17.00	17.18
		10.00	18.00	13.00	12.00	35.00	6.00	4.00	10.00	26.00	10.00	6.00	8.00	4.00	4.00	8.00	19.23	44.00	6.00	14.41
		20.00	40.00	25.00	35.00	65.00	50.00	30.00	30.00	70.00	20.00	10.00	10.00	30.00	0.00	30.00	50.00	60.00	6.00	33.04
		34.00	38.00	32.00	37.00	62.00	44.00	54.00	40.00	38.00	16.00	14.00	16.00	26.00	18.00	26.00	40.38	74.00	26.00	36.46
		41.00	46.00	33.00	39.00	68.00	52.00	56.00	44.00	44.00	26.00	26.00	28.00	24.00	10.00	24.00	34.62	80.00	38.00	40.71

Table A.2: Class-wise accuracy for Question Answering (QA) task evaluated using GPT-acc.

Models	Tasks	General Chart Types						Fine-grained Chart Types										Avg.		
		bar	bar ⁺	line ⁺	line ₊	pie	ring	box	hist	treemap	rose	area	3D-bar	bubble	multi	radar	heatmap	funnel		
Desc	Qwen-VL	1.58	1.30	1.80	1.75	2.40	1.60	1.50	1.70	1.90	1.50	1.70	1.50	1.60	1.80	1.30	1.60	1.90	1.30	1.67
	SPHINX-V2	1.36	1.60	1.50	1.75	2.35	1.60	1.00	1.10	1.70	1.80	1.30	1.20	1.40	1.60	1.30	1.20	1.80	0.70	1.53
	CharLlama	1.05	1.00	1.05	1.00	1.20	1.10	0.70	1.10	1.30	1.20	0.90	0.90	0.90	1.20	1.10	1.50	0.90	0.60	1.04
	CharAstr	0.00	0.40	0.25	0.15	2.00	0.90	0.40	0.00	0.00	0.60	0.00	0.00	0.00	0.00	0.00	0.00	0.20	0.00	0.34
	LLaVA-1.5	1.79	1.30	1.60	1.70	1.45	1.10	1.20	1.20	1.90	2.00	1.20	1.80	1.30	1.60	1.30	1.60	1.20	1.10	1.48
	GPT-4V	2.84	3.00	2.95	2.90	3.55	3.20	3.10	3.40	3.60	3.60	3.40	2.90	3.50	2.90	3.00	3.70	3.70	2.40	3.17
	CharVLM-B	1.95	2.70	2.05	1.90	3.90	2.40	2.00	2.40	2.60	1.60	1.70	1.70	1.30	2.50	2.00	2.60	2.40	2.40	2.05
	CharVLM-L	1.47	2.75	2.45	1.85	4.00	2.50	2.60	3.00	2.50	1.40	0.90	1.50	1.00	1.40	1.00	2.00	3.30	1.70	2.17

Table A.3: Class-wise accuracy for Chart Description (Desc) evaluated using GPT-score. The score of each individual description is an integer between 0-5.

Models	Tasks	General Chart Types						Fine-grained Chart Types										Avg.		
		bar	bar+num	line	line+num	pie	ring	box	hist	treemap	rose	area	3D-bar	scatter	multi	radar	heatmap	funnel	candle	
Summ	Qwen-VL	1.58	1.00	1.55	1.65	1.95	1.50	1.40	1.50	1.60	1.30	1.50	1.30	1.20	1.30	1.40	1.50	1.30	1.45	
	SPHINX-V2	1.16	1.00	1.10	2.50	1.40	1.40	1.50	1.40	1.40	1.10	1.10	1.10	1.10	1.10	1.10	1.10	1.10	1.39	
	CharLlama	1.05	1.00	0.95	1.25	1.00	1.00	1.00	1.30	1.10	1.20	0.80	1.00	0.70	0.60	1.30	1.00	0.70	1.20	1.02
	ChartArt	1.00	1.00	0.85	1.00	2.40	1.70	2.70	1.00	1.00	1.30	0.50	0.30	1.60	0.20	0.70	0.20	0.30	0.40	1.03
	LLaVA-L5	1.42	1.05	2.00	1.65	1.30	1.10	1.50	1.30	1.10	1.00	1.40	1.30	0.90	1.20	1.00	0.80	1.20	1.29	
	GPT-4V	3.10	2.80	3.20	2.75	3.30	3.10	2.70	4.00	3.50	3.60	2.40	2.70	3.00	3.10	3.10	4.10	3.60	2.70	3.12
	CharVLM-B	1.26	2.20	1.95	1.20	3.30	2.30	2.70	2.40	2.40	1.50	1.00	1.30	1.00	1.40	1.00	1.80	2.30	1.50	1.84
CharVLM-L	CharVLM-L	1.37	2.50	2.35	1.90	3.80	3.00	2.40	2.90	2.10	1.30	0.90	1.00	1.00	1.40	1.00	1.70	3.20	1.30	2.05

Table A.4: **Class-wise accuracy for Chart Summarization (Summ) evaluated using GPT-score.**
The score of each individual summarization is an integer between 0-5.

Models	Tasks	General Chart Types							Fine-grained Chart Types							Avg.				
		bar	bar+error	line	line+area	area	pie	ring	box	hist	treemap	rose	area3d	3D bar	multi	radar	heatmap	funnel	candle	
Redraw	Qwen-VL	0.89	0.60	0.80	0.80	1.25	1.10	0.80	0.80	0.80	1.10	0.60	0.60	0.60	0.80	0.60	0.50	0.70	0.86	
	SPHINX-V2	1.00	1.75	1.60	1.65	1.80	0.50	0.40	1.60	0.60	1.10	0.20	0.50	0.40	0.20	0.00	0.50	0.30	0.20	
	CharLlama	1.16	1.05	0.90	1.15	1.80	0.70	0.80	1.00	1.00	0.70	0.70	1.10	0.70	0.40	0.50	1.00	0.70	0.30	
	ChartArt	0.95	1.35	0.00	0.60	0.30	0.00	1.50	2.40	0.60	1.70	1.80	0.60	0.60	1.20	0.00	0.00	2.10	0.00	
	LLaVA-1.5	0.95	0.75	0.80	0.95	0.90	0.60	0.60	0.80	0.70	1.00	0.60	0.80	0.90	0.40	0.60	0.70	0.50	0.75	
	GPT-4V	2.05	2.70	2.05	2.75	3.55	3.40	2.00	2.70	2.70	2.80	2.20	2.70	2.40	2.80	2.30	3.20	3.50	1.60	2.63
	CharVLM-B	1.63	1.50	1.70	1.65	1.90	1.10	1.90	1.10	0.40	1.20	0.80	1.00	1.70	1.30	0.80	1.20	1.00	1.10	1.36
	CharVLM-L	1.53	1.85	1.85	1.70	2.75	1.90	1.40	1.20	0.90	1.00	1.10	1.60	1.30	1.50	0.80	1.90	1.20	1.10	1.58

Table A.5: **Class-wise accuracy for Chart Re-drawing (Redraw) evaluated using GPT-score.** The score of each individual redrawing code is an integer between 0-5.

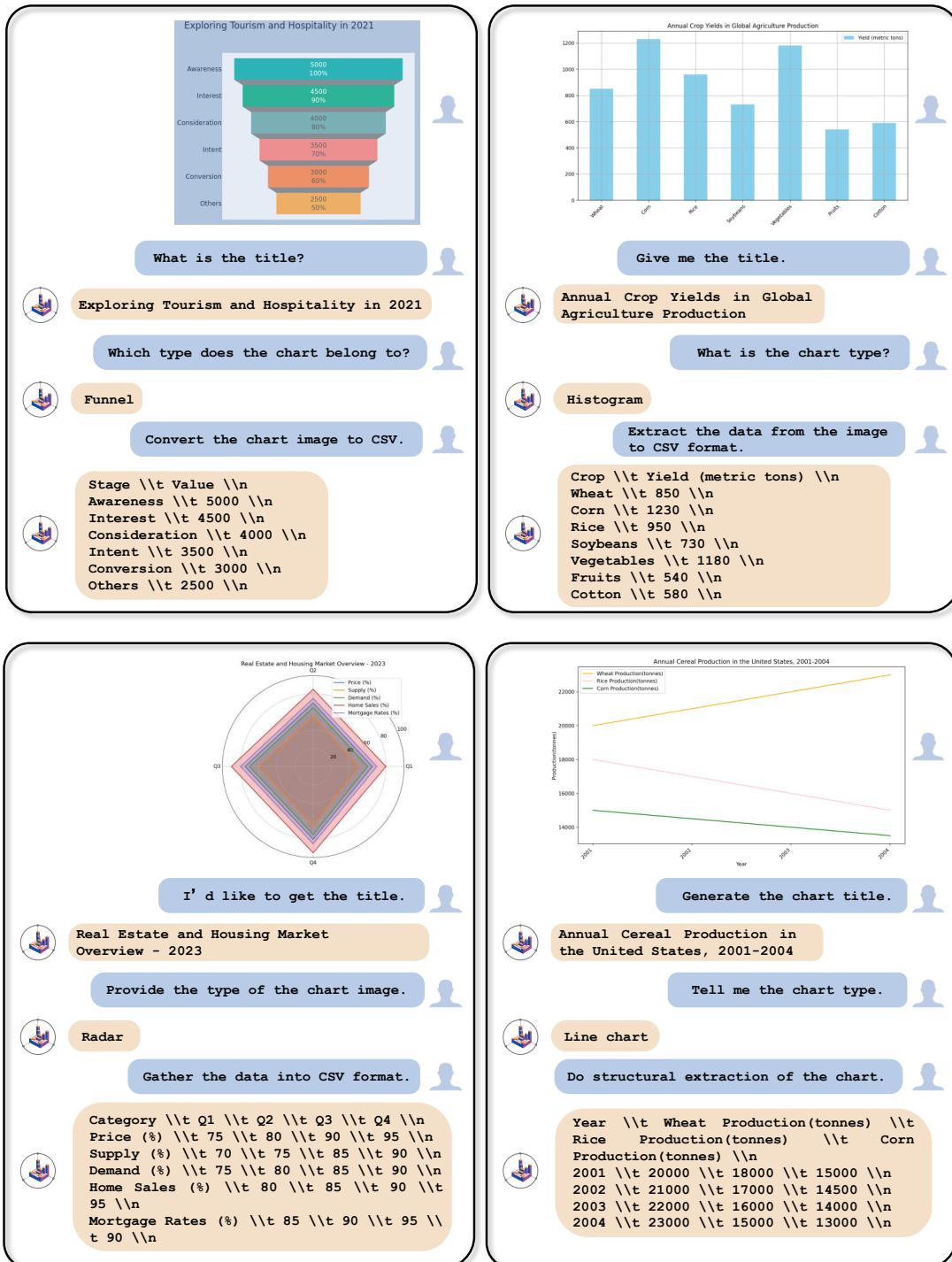


Figure A.7: More visualization results for perception tasks using ChartVLM, including Structural Extraction (SE), chart title, and chart type prediction tasks.