MMC: Advancing Multimodal Chart Understanding with Large-scale Instruction Tuning

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Abstract

With the rapid development of large language models (LLMs) and their integration into large multimodal models (LMMs), there has been impressive progress in zero-shot completion of user-oriented vision-language tasks. However, a gap remains in the domain of chart image understanding due to the distinct abstract components in charts. To address this, we introduce a large-scale MultiModal Chart Instruction (MMC-Instruction) dataset comprising 600k instances supporting diverse tasks and chart types. Leveraging this data, we develop Multi-Modal Chart Assistant (MMCA), an LMM that achieves state-of-the-art performance on existing chart QA benchmarks. Recognizing the need for a comprehensive evaluation of LMM chart understanding, we also propose a Multi-Modal Chart Benchmark (MMC-Benchmark), a comprehensive human-annotated benchmark with 9 distinct tasks evaluating reasoning capabilities over charts. Extensive experiments on MMC-Benchmark reveal the limitations of existing LMMs on correctly interpreting charts, even for the most recent GPT-4V model. Our work provides an instruction-tuning methodology and benchmark to advance multimodal understanding of charts.

1 Introduction

Large Language models (LLMs) such as GPT-3, PaLM, ChatGPT, Bard, and LLaMA (Brown et al., 2020; Chowdhery et al., 2022; OpenAI, 2022; Manyika, 2023; Touvron et al., 2023) have undergone rapid development, demonstrating significant capabilities in performing a wide range of tasks effectively. To enable LLMs with vision ability, open-source large multimodal models (LMMs) such as MiniGPT-4 (Zhu et al., 2023), LLaVA (Liu et al., 2023d), mPLUG-Owl (Ye et al., 2023), Multimodal-GPT (Gong et al., 2023), and LRV (Liu et al., 2023b) have been developed, incorporating advanced image understanding capabilities into LLMs to interpret and analyze visual in-

puts. While successful in the general domains, such open-source LMMs are less effective for chart images because chart image understanding is tremendously different from natural scene image understanding. Contrasting with natural scene images, which primarily contain objects and reflect their spatial relationships, chart images contain unique abstract elements (such as flow diagrams, trend lines, color-coded legends, etc.) that convey specific data-related information.

Current open-source LMMs are limited in their ability to accurately interpret complex chart contents, as they often lack domain-specific training essential for tasks such as differentiating between various types of graphs, interpreting axis labels and data points, and extracting meaningful patterns and trends. integrating advanced chart understanding capabilities could further refine the LMMs' ability to analyze contextually and reason about the information presented in charts, thereby broadening their applicability in fields like data analytics, academic research, and business intelligence.

In this paper, we introduce MultiModal Chart Instruction (MMC-Instruction), a 600k chart understanding dataset consisting of both chart-text alignment data and chart instruction-tuning data. MMC-*Instruction* is not only much larger but also more diverse compared to existing public datasets (Kahou et al., 2017; Masry et al., 2022; Methani et al., 2020; Kafle et al., 2018). Unlike previous work with templated-based questions, MMC-Instruction is constructed by prompting GPT-4 to generate instructions with diverse language styles and tasks (Table 1). Furthermore, our MMC-Instruction considers a variety of chart types, including but not limited to histograms, scatter plots, area charts, and more complex graphical representations. By performing unified instruction tuning upon current LMMs with *MMC-Instruction*, we further propose a modularized LMM, namely Multimodal Chart Assistant (MMCA), jointly finetuned on a wide range

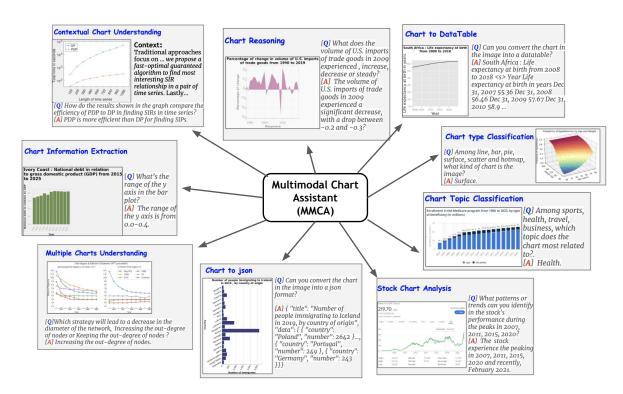


Figure 1: Diagram of our human-annotated *MMC-Benchmark*, consisting of 9 distinct tasks, various topics (*business*, *health*, *biology*, *engineering*, *etc*), free-form questions, open-ended answers, and unbounded plot types.

Datasets	Figure Num	Question	Answer Type	Plot Type	Task Num	Benchmark
FigureQA	180k	Template	Fixed Vocab	4	1	×
DVQA	300k	Template	Fixed Vocab	1	1	×
PlotQA	224k	Template	Fixed	1	1	×
ChartQA	21.9k	Free-form	Open Vocab	Unbounded	2	Human Check
SciGraphQA	295k	Free-form	Open Ended	Unbounded	2	×
MMC-Instruction (Ours)	600k	Free-form	Open Ended	Unbounded	9	Human Check

Table 1: Comparison between *MMC-Instruction* with existing chart-based question-answering datasets. *MMC-Instruction* is larger, more diverse, and more trustworthy.

of visually situated language understanding tasks. *MMCA* achieves state-of-the-art performance on current chart question-answer benchmarks compared with existing open-source LMMs.

To accurately assess the capabilities of current Large Multimodal Models (LMMs) for chart understanding, we introduce a novel comprehensive evaluation tool: the MultiModal Chart Benchmark (MMC-Benchmark). First, MMC-Benchmark is the first human-annotated benchmark in line with human cognition to evaluate LMM's ability to comprehend visual charts. Second, it contains a wide range of tasks, including chart information extraction, chart reasoning, contextual chart understanding, chart topic classification, stock chart analysis, multiple chart understanding, chart type classification, chart-to-datatable and chart-to-json. Third, MMC-Benchmark offers two quantitative evaluation methods, including free-format Generation

Ability Evaluation using ChatGPT and multiple-choice QA format Chart Understanding Ability Evaluation without the requirement of ChatGPT. Our evaluation highlights the limitations of existing open-source LMMs. In addition, we further broaden our analysis through experiments with GPT-4V (OpenAI, 2023b; Yang et al., 2023b; Liu et al., 2023a), the latest multimodal version of GPT-4 (OpenAI, 2023a). Our experiments indicate that *MMC-Benchmark* also poses significant challenges to GPT-4V, especially in *Chart to Datatable* and *Chart to Json* tasks. It indicates the importance of *MMC-Instruction* corpus and *MMC-Benchmark* in advancing multimodal understanding.

Our main contributions are as follows:

• MMC-Instruction dataset. We present a novel large-scale instruction-tuning dataset for chart understanding. It includes diverse topics, language styles, chart types, and open-ended answers in line with human cognition.

- MMC-Benchmark. We present a manually annotated benchmark specifically designed to assess the capability of LMMs in chart understanding across nine distinct sub-tasks to ensure a comprehensive evaluation.
- MMCA model. We propose an instructiontuned LMM model that outperforms existing open-source state-of-the-art (SoTA) LMMs for chart understanding on both existing chart understanding benchmarks and our proposed benchmark.

Our data and code will be available at this repo ¹.

2 Related Work

Multimodal Large Language Model. Recently, Large Language Models (LLMs) have shown strong performances in zero-shot tasks across multiple domains. Recent studies explore using LLMs for multi-modal task completion. One direction (Wu et al., 2023a; Yang et al., 2023c,a) uses Chat-GPT as the intermediary to choose the best tools or experts for visual interpretation according to user's inquiries. Another direction is end-to-end training (Zhu et al., 2023; Liu et al., 2023d,b; Ye et al., 2023; Yin et al., 2023; Wu et al., 2023b; Zhang et al., 2023; Cao et al., 2023; Zhai et al., 2023) utilizing LLMs and visual encoders to create integrated models for multimodal tasks with inter-connected parameters to relate them. These existing approaches perform well on general visual and language tasks like image captioning and visual question answering with strong language skills. However, when it comes to chart understanding, they often fall short due to a lack of specific training to bridge the chart information with the textual content. Our work enhances visual chart understanding by introducing a novel chart visual instruction-tuning corpus and chart understanding model.

Chart Text Understanding. Another line of research (Kantharaj et al., 2022; Masry et al., 2023; Lee et al., 2023) is to train a high-resolution image encoder on a large image-text pair corpus to learn text recognition during the pretraining stage. However, these models rely on specific finetuning on different downstream datasets and cannot achieve open-domain multi-task understanding like LLMs or LMMs do. Earlier datasets such as (Kahou

et al., 2017; Chaudhry et al., 2020; Methani et al., 2020; Masry et al., 2023; Liu et al., 2020, 2023c) primarily rely on synthetic data, with templategenerated questions and answers selected from a fixed vocabulary. More recently, ChartQA (Masry et al., 2022) utilizes real-world, web-crawled charts to develop its visual question-answering datasets, supplemented by human annotators. However, it mainly focuses on compositional and visual questions. (Li and Tajbakhsh, 2023) uses Palm-2 to generate question-answering data for academic charts. However, the answers generated by Palm-2 contain hallucinations. Comparatively, the advantages of our dataset come from its larger size, more diverse topics, richer language styles, and good quality.

3 MMC-Instruction

3.1 Chart-Text Alignment Data

To build a large training corpus for chart-text alignment with a diverse range of styles and topics, we aim to collect chart and text data from online sources. We first collect the *Scientific Chart-Caption* corpus with both chart and text crawled from arXiv. In addition, we utilize several existing public chart datasets that are suitable for chart-text alignment. The collected charts can be categorized into multiple topics, including computer science, business, health, biology, agriculture, etc.

Scientific Chart-Caption data collected by us. We first download the academic articles (2010-2020) through an official dump from the arXiv website. It is licensed under CC-0, which grants remake and republish rights. Unlike (Hsu et al., 2021) using PDFs, we utilize the source files containing the original LaTeX and figure files. In order to improve the dataset quality, we removed the source files without LaTeX or figure files and the source files that are hard to parse. We only keep the chart figures with rich text information in the captions by deleting the pairs whose caption length is less than 25 tokens.

Leveraging Existing Datasets. For chart-text alignment training with diverse chart caption data, we further include the following five public chart datasets for which the underlying data tables are available: (i) Statista (Kantharaj et al., 2022), (ii) PlotQA (Methani et al., 2020), (iii) VisText (Tang et al., 2023), (iv) ChartInfo (Lal et al., 2023), (v) Unichart (Masry et al., 2023).

¹https://github.com/FuxiaoLiu/MMC

3.2 Chart Instruction-Tuning Data

This section introduces the construction of our instruction tuning data in detail. To align the model to follow a variety of instructions, we construct diverse instruction-tuning instances about the provided chart images by prompting the language-only GPT-4. Specifically, given a chart description, we design instructions in a prompt that asks GPT-4 to generate questions and answers in a style as if it could see the image (even though it only has access to the text). The prompt examples for GPT-4 are shown in Fig. 17, 18, 19, 20. Our instructiontuning data is formatted as: "Human: {question} AI: {answer}". MMC-Instruction includes the following tasks: chart information extraction, chart reasoning, scientific chart understanding, chart-todatatable, and chart-to-json. Examples of our chart instruction-tuning data are shown in Fig. 1 and Fig. 5, 6, 7, 8, 9, 10, 11, 12 in the Appendix.

Chart Information Extraction requires the model to extract from the input chart detailed information such as title, coordinate value, scope, trend, etc. To achieve this goal, we collect the generated L1 captions from (Tang et al., 2023), whose content enumerates aspects of the chart's construction. Then, we ask GPT-4 to generate question-answer pairs about the detailed construction information about the chart given L1 captions. In addition, we require the generated answers to be less than 20 words to address hallucination (Liu et al., 2023b).

Chart Reasoning requires the model to analyze and identify data patterns, relationships, and anomalies of the input chart. To achieve this goal, we collect the generated L2/L3 captions from (Tang et al., 2023), which summarize the statistics and synthesize the cognitive phenomena of the chart. Then, we ask GPT-4 to generate question-answer pairs that require analysis skills.

Scientific Chart Understanding is a challenging task that needs scientific background knowledge. To create instruction-tuning data, we combine the abstract, title, and image captions of arXiv papers to construct the comprehensive textual context. Sometimes, the image caption is too short for GPT-4 to generate meaningful questions and answers regarding the image. To provide more context regarding the image, we also create a prompt that includes paragraphs mentioning the figure in the paper. From our observation, we find a portion of the questions are not graph-related but a follow-up on the textual context in previous an-

swers. Hence, we use heuristic rules to delete the non-chart-related questions.

Chart-to-DataTable and Chart-to-Json are the tasks of transforming the visual information represented in the chart into the structured data format of a table or a JSON. This process typically requires interpreting the graphical elements of the chart, such as bars, lines, or pie segments, quantifying their values, and then organizing these values into a tabular format that accurately reflects the original chart.

4 MultiModal Chart Assistant (MMCA)

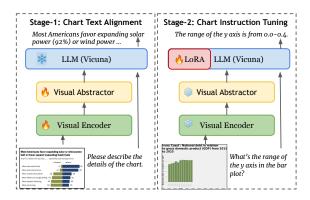


Figure 2: The overall architecture of MMCA, which is continuously trained in two stages.

Architecture. Our model Multimodal Chart Assistant (MMCA) is built on top of the most recent multimodal architectures (e.g., mPLUG-Owl (Ye et al., 2023)), MiniGPT4 (Zhu et al., 2023)) that guide LLMs to follow multimodal instructions. In order to improve the existing LLMs to perform better on chart understanding tasks, we further finetune mPLUG-Owl 7B (Ye et al., 2023)) on our proposed MMC-Instruction corpus consisting of Chart-Text Alignment Data and Chart Instruction-Tuning Data. mPLUG-Owl contains a pre-trained visual foundation model (CLIP vision encoder), a visual abstractor, and a language foundation model (Vicuna). The visual foundation model is responsible for extracting visual features from the input images, and the visual abstractor distills these features using a set of learnable tokens. The resulting visual features are then concatenated with the word embeddings of the input sentence and fed into the language model to generate the response. We incorporate a two-stage training paradigm.

Stage-1: Chart Text Alignment. In this stage, we freeze both the visual encoder and the language decoder and train the visual abstractor with our

Category	Image Source	Question Source	Question Type	Number	Human Check
Chart Information Extraction	Statista.com	GPT4	Free-form/MQA	330	V
Chart Reasoning	Statista.com	GPT4	Free-form/MQA	256	✓
Contextual Chart Understanding	arxiv	GPT4, human	Free-form/MQA	56	✓
Multiple Chart Understanding	arxiv	GPT4, human	Free-form/MQA	52	✓
Chart Type Classification	Web Crawl	Groundtruth label	Free-form/MQA	360	✓
Chart Topic Classification	Web Crawl	Groundtruth label	Free-form/MQA	536	✓
Chart To DataTable	VisText	Source Article	Free-form/MQA	400	✓
Chart To Json	VisText	GPT4	Free-form/MQA	96	✓
Stock Chart Analysis	Google Bard	Source Article	Free-form/MQA	40	✓

Table 2: Key statistic and composition of MMC-Benchmark. MQA means multiple-choice questions.

Chart-Text Alignment Data for 1 epoch. This stage enables the mapping of visual features of charts to LLM's word embedding space.

Stage-2: Chart Instruction Tuning. In the second stage, we freeze the visual abstractor, visual encoder, and language decoder and use the lowrank adaptation approach (LoRA) (Ye et al., 2023) to fine-tune the language model. Specifically, we train the language model with LoRA on our *Chart Instruction-Tuning Data* for 3 epochs. The training hyper-parameters are the same as (Ye et al., 2023). This stage enables LLM's instruction following capabilities for chart understanding.

5 MMC-Benchmark

The recent progress of LMMs has enabled the open-ended zero-shot completion of user-oriented vision-language tasks such as open-ended chart understanding. As a result, a comprehensive evaluation benchmark is necessary to evaluate the performances of different LMMs on these tasks and provide quantitative guidance for future research and development. However, for chart understanding, existing benchmarks often fall short of evaluating open-ended questions and unbounded chart types. Our dataset, MMC-Benchmark, is therefore motivated to bridge this gap, offering three unique characteristics for chart understanding: (i) MMC-Benchmark is the first benchmark with human annotations to evaluate LMM's ability to comprehend visual charts. (ii) MMC-Benchmark is more diverse with various sources and nine different tasks, including chart information extraction, chart reasoning, contextual chart understanding, multiple chart understanding, chart type classification, chart topic classification, chart-to-datatable, chartto-json, and stock chart analysis, with examples shown in Fig.1. (iii) MMC-Benchmark provides two evaluation methods for convenient quantitative analysis, including free-format Generation Ability Evaluation using ChatGPT and multiple-choice

QA format Chart Understanding Ability Evaluation without the requirement of ChatGPT. The statistic of *MMC-Benchmark* is shown in Tab. 2.

Data Collection. For chart information extraction and chart reasoning tasks, the images are samples from (Masry et al., 2022), but the instructionanswer pairs are all manually constructed by us rather than from existing public annotations. For contextual chart understanding and multiple chart understanding, we collect the source images from scientific charts of arXiv that are not presented in our training sets. Contextual chart understanding requires the models to read the context information to answer the questions of the charts. We utilize the abstract of the scientific paper as the context information. We manually design the questions for the multiple chart understanding, which evaluates the model's complex reasoning ability to compare between multiple charts. The chart type classification task contains six types: line, bar, pie, scatter, heatmap, and surface. The images of line, bar, and pie chart are from (Methani et al., 2020) while others are collected by us from Google Bard. The chart topic classification task includes health, business, computer science, travel, and sports, whose images are crawled from Google. As for the chartto-datatable and chart-to-json tasks, we use the images and data tables from (Wu et al., 2023a). The json data is generated by prompting GPT-4 with the datatable as the input. Finally, for stock chart analysis, we collect the chart images of stock from Google Bard without including corresponding captions due to hallucination concerns. Instead, we look through the source article and manually construct the questions about the stock trend, predictions, and corresponding background knowledge.

Evaluation Protocols. In order to evaluate LMMs' generation ability and chart understanding ability, the instructions in *MMC-Benchmark* consists of two parts. (1) *Generation Ability Evaluation*, which utilizes ChatGPT to compare between

reference answers and generated texts. The prompt we used for evaluation is shown in Fig. 3, where we provide ChatGPT with the question, the reference answer, and the model prediction and ask ChatGPT to assess the accuracy of the model prediction. (2) *Understanding Ability Evaluation*, which aims to let the model select the correct answer from multiple choice questions (MQA) given in the chart. For each image, we manually design choices for each question. Unlike *Generation Ability Evaluation*, *Understanding Ability Evaluation* does not require the utilization of ChatGPT.

6 Experiments

6.1 Experimental Setup

Our *MMCA* model is trained with 8 Nvidia Tesla V100 GPUs. We compare *MMCA* with existing models in three setups: (a) Open-source LMMs including MiniGPT4-7B (Zhu et al., 2023), mPLUGowl-7B (Ye et al., 2023), LRV-Instruction (Liu et al., 2023b), LLaVA-7B (Liu et al., 2023d), and Multimodal-GPT-9B (Gong et al., 2023). (b) GPT-4V (OpenAI, 2023b) recently released by OpenAI. (c) Non-LLMs based models including Pix2Struct (Lee et al., 2023) and Donut (Kim et al., 2022).

6.2 Experiment Results

6.2.1 Evaluation Results on MMC-Benchmark

As indicated in Tab. 3 and Tab. 4, MMCA achieves better performance in all 9 tasks in comparison with the existing open-source models. The improvement of MMCA demonstrates the effectiveness of our MMC-Instruction data in enabling the LMM to complete chart understanding tasks. In addition, we find that current LMMs are better at understanding cross-modality relationships in the image but weaker at comprehending text layout information. This can be attributed to their lack of text recognition, scientific knowledge, and math reasoning abilities. The weak performance of MiniGPT4 can be attributed to its limited instruction-tuning data with a single task in a small size. Though finetuned with instruction-tuning data from text-rich images, LLAVa and mPLUG-owl do not perform well, indicating that strong text recognition abilities in images do not guarantee high performance on MMC-Benchmark, which requires comprehensive visual perception and chart reasoning capability.

Additionally, current LMMs perform badly on the *chart-to-datatable* and *chart-to-json* tasks. We conjecture that it is due to the fact that these two tasks require strong OCR ability to output all the data values in the chart correctly. If one value is missing, the prediction will be regarded as incorrect. Besides, we also find that the overall performance of *Multiple Chart Understanding* is lower than *Contextual Chart Understanding*. This phenomenon may be attributed to the lack of training data with multiple images as input.

6.2.2 Results on Public Benchmarks

We compare our *MMCA* with the state-of-the-art methods on existing public benchmarks including ChartQA (Masry et al., 2022), DocVQA (Mathew et al., 2021), and TextVQA (Yang et al., 2021). As shown in Tab. 5, our *MMCA* outperforms existing LMMs, including MiniGPT4 and LRV-Instruction on the three public benchmarks. Moreover, without including any finetuning on the corresponding datasets, our proposed *MMCA* model outperforms both Pix2Struct and Donut that are finetuned on these datasets. Such results validate that with the help of open-domain large multi-modal models (LMMs), the performance of chart understanding can be significantly improved.

6.2.3 Comparison with GPT-4V

We further evaluate and benchmark GPT-4V (OpenAI, 2023b) via the "gpt-4-vision-preview" model on our proposed MMC-Benchmark. In our queries to GPT-4V, we prepend the prompt with "Generate a short and concise response to the following image text pair." The quantitative results are shown in Tab. 3. Remarkably, GPT-4V surpasses all opensource LMMs by substantial margins on seven out of the nine tasks of MMC-Benchmark. Such results prove GPT-4V's strong skills in text recognition, scientific knowledge, and math reasoning. The only two tasks GPT-4V performs poorly are Chart to Datatable and Chart to Json. As shown in Fig.16, GPT-4V misrecognizes the data value from the charts. Apart from the two tasks, GPT-4V may predict incorrectly on the Multiple Charts Understanding tasks such as Fig. 14, 15. Other failure examples are shown in Fig. 4. As indicated by (Liu et al., 2023a), the strong language prior misled GPT-4V to answer "China appears to be the third largest country by land area in the world", which conflicts with the information mentioned in the chart "USA appears to be the third largest country by land area in the world". This MMC-Benchmark analysis is intended as a source of inspiration for future research, specifically in the realms of advanced

Imagine you are an intelligent teacher. Thoroughly read both the reference answer and the prediction answer to ensure a clear understanding of the information provided. Assess the accuracy of the predictions, and note that a prediction answer will be considered incorrect if it contradicts the reference answer.

Question: What does the volume of U.S. imports of trade goods in 2009 experienced, increase, decrease or steady?

Reference answer: The volume of U.S. imports of trade goods in 2009 experienced a significant decrease, with a drop between -0.2 and -0.3.

Prediction answer: The volume of U.S. imports of trade goods experienced a decrease.



experienced a significant decrease". Therefore, the

prediction answer is correct.

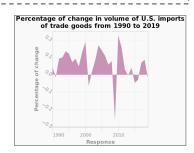


Figure 3: An example of Generative Ability Evaluation by *text-only ChatGPT*. In the prompt, we provide *ChatGPT* with the question, reference answer, and predictions from models.

Free-form Evaluation	LLAVA	MiniGPT4	mPLUG-owl	LRV-Instruct	MMCA(Ours)	GPT-4V
Chart Information Extraction	0.29	0.23	0.27	0.24	0.35	0.63
Chart Reasoning	0.28	0.20	0.22	0.19	0.30	0.57
Contextual Chart Understanding	0.30	0.21	0.28	0.23	0.33	0.55
Multiple Chart Understanding	0.24	0.17	0.23	0.21	0.29	0.39
Chart Type Classification	0.27	0.20	0.25	0.22	0.31	0.79
Chart Topic Classification	0.31	0.19	0.24	0.21	0.32	0.82
Stock Chart Analysis	0.24	0.18	0.25	0.23	0.32	0.70
Chart to Datatable	0.00	0.00	0.05	0.00	0.08	0.05
Chart to Json	0.01	0.00	0.00	0.00	0.05	0.04

Table 3: *MMC-Benchmark* evaluation results on LLaVA, MiniGPT4, mPLUG-Owl, LRC-Instruct, MMCA, and the recent GPT-4V regarding the Generation Ability Evaluation. Given the reference response, we apply *ChatGPT* to determine the correctness/incorrectness (as in Fig. 3) of the response for each test sample. The ratio of correct responses out of responses for all test samples in each task is used for evaluation.

multimodal prompting techniques and model refinements to improve the LMM performance further.

The strength and weakness of the closed proprietary GPT-4V model shown in our *MMC-Benchmark* evaluation further proves the value of our proposed *MMC-Instruction* corpus for the open-source community to improve LMMs for chart understanding. As shown in Table 3 & 4, our *MMC-Instruction* corpus helps to significantly improve *MMC-Benchmark* performances over existing public LMMs by a large margin in all nine tasks. This corpus can be applied in future open-source LMMs to boost their chart understanding performance. Moreover, our work demonstrates a part of the weakness areas of the GPT-4V model, and the *MMC-Instruction* corpus provides instruction tuning data for future closed proprietary and

open-source models to tackle such weaknesses.

6.3 Discussions

We summarize four common problems affecting the performance of existing large multimodal models (LMMs) like MiniGPT4, etc.

Not Following Instructions. Even with a very concise instruction design, there are LMMs that do not follow the user's instructions. For example, in Fig. 21a of the Appendix, when asked "Please identify the proportion of Americans who favor the coal mining.", Pix2Struct and Unichart answer "Yes" and "the proportion of Americans who favor coal mining.", respectively. Additionally, in Fig. 21a(a), MiniGPT4 makes a declarative expression without answering whether light green is the maximum or not. In our opinion, a good chart understand-

MQA Evaluation	LLAVA	MiniGPT4	mPLUG-owl	LRV-Instruct	MMCA(Ours)
Chart Information Extraction	0.41	0.39	0.45	0.45	0.49
Chart Reasoning	0.37	0.35	0.44	0.41	0.47
Contextual Chart Understanding	0.45	0.34	0.50	0.42	0.55
Multiple Chart Understanding	0.40	0.32	0.43	0.45	0.47
Chart Type Classification	0.51	0.48	0.55	0.50	0.59
Chart Topic Classification	0.50	0.52	0.54	0.51	0.64
Stock Chart Analysis	0.45	0.46	0.45	0.45	0.57
Chart to Datatable	0.33	0.40	0.44	0.35	0.64
Chart to Json	0.35	0.39	0.41	0.39	0.59

Table 4: *MMC-Benchmark* evaluation results on LLaVA, MiniGPT4, mPLUG-Owl, LRC-Instruct, and our MMCA regarding the Understanding Ability Evaluation via *Multichoice QA* (MQA) task. We calculate the accuracy of the model predictions in the MQA setting. There is no need to call *ChatGPT* for this evaluation.

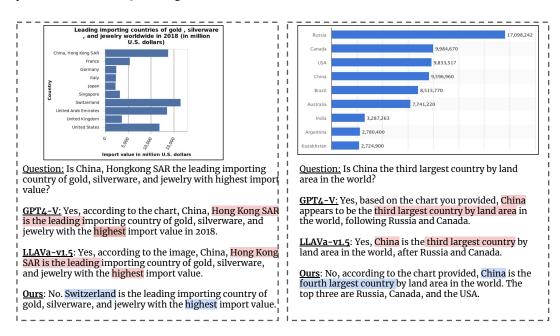


Figure 4: Failure examples of GPT4-V and LLAVa-v1.5. RED highlights the hallucinations from GPT-4V and LLAVa-v1.5. BLUE highlights the correct answers from our model.

Model	ChartQA	DocVQA	TextVQA
Donut	41.8	67.5	43.5
Pix2Struct	56.0	72.1	-
MiniGPT4	46.5	42.3	-
LRV-Instruction	47.5	58.5	-
MMCA(Ours)	57.4	72.5	57.6

Table 5: Comparison with OCR-free methods and LMMs on existing public benchmarks.

ing model should be able to follow instructions. However, to the best of our knowledge, most of the existing LLM-based or LMM-based models, except for GPT-4V, are not able to follow human instructions for chart understanding well.

Vision Encoder is Weak. Existing LMMs typically use CLIP as the vision encoder and do not update its parameters during training. However, as CLIP is trained to align visual embeddings with

short captions, its capability on modeling the spatial interactions of chart elements like trend lines and color-coded legends is limited. On the other hand, such capabilities are essential to identify specific legends, trends, or labels in the chart. The potential method is to add segmentation (Kirillov et al., 2023) and project the segments into the LLM token embedding space. Instead, in our proposed *MMCA* approach, we finetune LMMs on our *MMC-Instruction* data by updating the vision projector during training and improving the integration of visual elements into the LLM input domain. The improvements in our experiments demonstrate the effectiveness of our proposed *MMC-Instruction* dataset and the training strategy in *MMCA*.

MMC-Benchmark is more Challenging than Previous Benchmarks. From Tab. 3, we find that the overall scores for existing models on *MMC*-

Benchmark are relatively lower than those on the current benchmarks like ChartQA. Such results are expected since the questions in MMC-Benchmark are more diverse, and the answers are open-ended. Additionally, MMC-Benchmark contains more topics that require both a comprehensive understanding of charts and proficient language skills.

Chart-to-DataTable and Chart-to-Json are extremely Difficult. As shown in Tab. 3, all current LMMs, including GPT-4V, perform badly on these two tasks. It is probably due to the fact that these two tasks require strong OCR skills to output all the data values in the chart correctly. If one value is missing, the prediction will be regarded as incorrect. Compared with baselines in Fig. 21a, our MMCA model is able to produce more accurate responses in correct output formats.

7 Conclusion

This paper aims to tackle the challenge of chart understanding with Large Multimodal Models (LMMs). Firstly, we present a novel and largescale chart instruction-tuning dataset called MMC-*Instruction* that includes diverse topics, language styles, chart types, and open-ended answers in line with human cognition. Secondly, we introduce a human-annotated benchmark called MMC-Benchmark to evaluate LLMs' abilities for chart understanding quantitatively. We also conduct abundant experiments on a total of nine subtasks to comprehensively evaluate LMMs. Finally, we propose an instruction-tuned LMM called MMCA that outperforms existing open-source state-of-the-art (SoTA) methods on both well-established chart understanding datasets and MMC-Benchmark.

Though we believe *MMCA* represents a significant step toward building a useful multimodal chart assistant, we notice *MMCA* is limited by a weak vision encoder and preliminary performance on *chart-to-datatable* and *chart-to-json* tasks. Future work is directed toward overcoming the challenges with advanced visual encoding and modeling.

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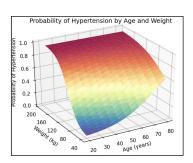
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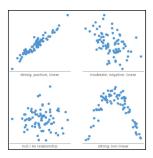
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A Appendix



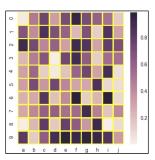
Among line, bar, pie, surface, scatter and heatmap, what kind of chart is the image? Answer:



Question:

Among line, bar, pie, surface, scatter and heatmap, what kind of chart is the image?

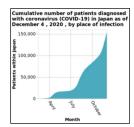
Answer:



Question:

Among line, bar, pie, surface, scatter and heatmap, what kind of chart is the image? Answer:

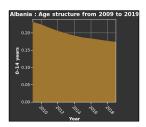
Figure 5: Examples of the Chart Type Classification Task



Question:

What does the y-axis represent? Answer:

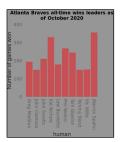
Number of COVID-19 patients within Japan, ranging from 0 to 150,000.



Question:

What is the name of the area diagram? Answer:

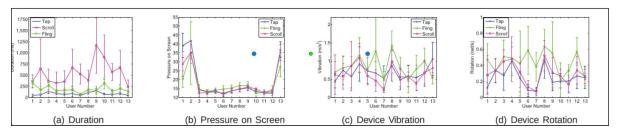
Albania: Age Structure from 2009 to



How many games did Warren Spahn win? Choices: A) 250 games B) 350 games? Answer:

B) 350 games.

Figure 6: Examples of the Chart Information Extraction Task

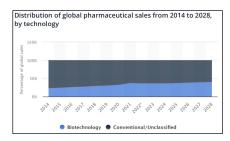


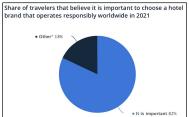
Question:

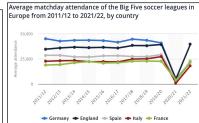
What is the purpose of the graph that highlights the variations in interacting features among different user numbers in the static scenario? a) To illustrate the uniqueness and diversity of behavior biometric b) To showcase the similarities and commonalities of behavior biometric c) To analyze the impact of user numbers on behavior biometric"

Answer:To illustrate the uniqueness and diversity of behavior biometric

Figure 7: Examples of the Multiple Charts Understanding Task







Among sports, health, travel, business, which topic is the chart most related to?

Answer:

Health

Question:

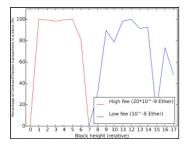
Among sports, health, travel, business, which topic is the chart most related to?

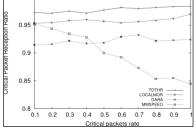
Answer:

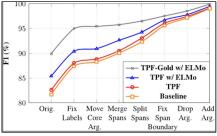
Question:

Among sports, health, travel, business, which topic is the chart most related to? Answer:

Figure 8: Examples of the Chart Topic Classification Task







Ouestion: What is the purpose of this graph?

To illustrate the relationship between transaction fees and blockchain availability Four different algorithms

Ouestion:

What does the graph compare in terms of packet reception ratio for critical packets?

Answer:

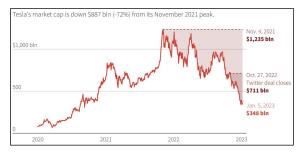
Ouestion:

How do the oracle transformations enhance the CoNLL-2005 models?

Answer:

By applying operations that correct errors in

Figure 9: Examples of the Arxiv Chart Understanding Task

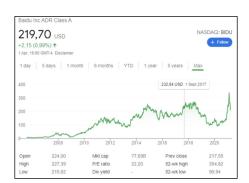


Question:

What has been the trend of the stock price from January 2021 until 2022?

Answer:

The trend of the stock price from January 2021 until 10/01/22 is upward



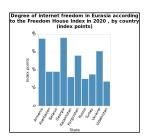
Ouestion:

BAIDU stock has also been very volatile. You see the stock peaking in 2007, 2011, 2015, 2020 and recently, February 2021, only to crash after and stay down for a few years. Is this statement true or false?

Answer:

Yes. The statement is correct.

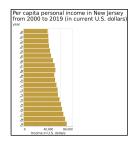
Figure 10: Examples of the Stock Charts Analysis Task



Is the level of freedom in Russia higher, lower, or equal to that of Georgia?

Answer:

The level of freedom in Russia is lower than Georgia.

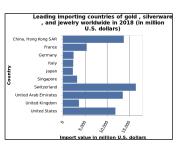


Question:

What has the per capita income in New Jersey shown from 2000 to 2019?

Answer:

A steady upward trend.



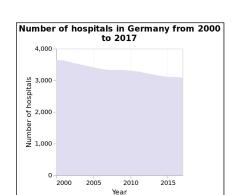
Question:

Which country is the top importer among Switzerland, UAE, and China?

Answer:

Switzerland

Figure 11: Examples of the Chart Reasoning Task



Question:

Can you convert the chart in the image into a json format? **Answer**:



Figure 12: Examples of the Chart to Json Task



Question:

The stock price is trading within a narrow range, which is a neutral signal. Is it true or false?

GPT-4V Output:

In technical analysis, trading within a narrow range indicates that the market is consolidating, and it doesn't give a clear signal about a bullish (positive) or bearish (negative) trend until a breakout occurs above the resistance or below the support level. Therefore, saying that the stock price is trading within a narrow range is a neutral signal is true. It suggests that investors are waiting for more definitive information that could push the stock out of the range in either direction.



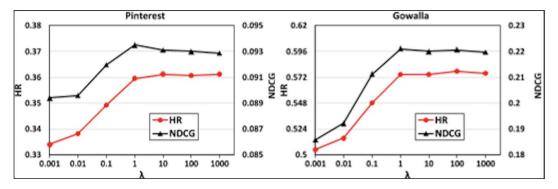
Question:

The stock price is trading within a narrow range, which is a neutral signal. Is it true or false?

GPT-4V Output:

The statement you've provided about the stock price trading within a narrow range being a neutral signal is not supported by the image you've uploaded. The image actually shows a chart with a descending trendline, indicating that the stock has been experiencing a downtrend. The trendline is drawn above the price bars, showing that the highs of the price bars are getting lower over time. This is typically considered a bearish signal, not a neutral one. So, the statement is false based on the information provided in the image. The chart depicts a downtrend, not a stock trading within a narrow range.

Figure 13: GPT-4V works well on Stock Chart Analysis task.



What happens when λ is smaller than 1 in terms of the performance of AMF? Choices:A) Decreasing λ leads to gradual improvements in the performance of AMF.B) Increasing λ leads to gradual improvements in the performance of AMF.C) The performance of AMF remains the same when λ is smaller than 1.

GPT-4V Output:

From the graphs, we can observe the following trends for values of λ smaller than 1:

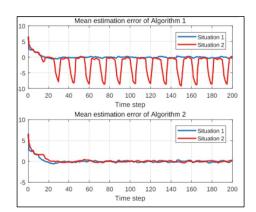
For the Pinterest dataset, as λ decreases from 1 to 0.001, both HR and NDCG metrics increase, which indicates that the performance of AMF improves.

For the Gowalla dataset, similarly, as λ decreases from 1 to 0.001, the HR and NDCG also increase, suggesting improvement in performance.

Based on these observations, the correct answer is:

A) Decreasing λ leads to gradual improvements in the performance of AMF.

Figure 14: Failure cases of GPT-4V on *Multiple Chart Understanding* task. RED means the incorrect answers from GPT-4V

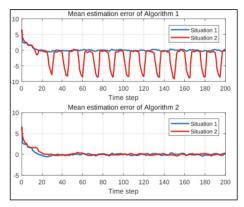


Question:

According to the graph, which of the following statements accurately describes the bias of Algorithm 1 and Algorithm 2 under Situation 1? Choices:A) Algorithm 1 is asymptotically biased while Algorithm 2 is unbiased.B) Both Algorithm 1 and Algorithm 2 are asymptotically biased.C) Both Algorithm 1 and Algorithm 2 are asymptotically unbiased.

GPT-4V Output:

Given the observations, the correct choice would be: C) Both Algorithm 1 and Algorithm 2 are asymptotically unbiased.



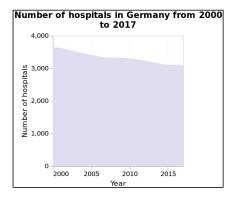
Question:

According to the graph, which of the following statements accurately describes the bias of Algorithm 1 and Algorithm 2 under Situation 1? Choices: A) Algorithm 1 is asymptotically biased while Algorithm 2 is unbiased. B) Both Algorithm 1 and Algorithm 2 are asymptotically unbiased. C) Both Algorithm 1 and Algorithm 2 are asymptotically biased.

GPT-4V Output:

Based on this analysis, the correct answer would be: A) Algorithm 1 is asymptotically biased while Algorithm 2 is unbiased.

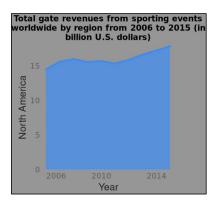
Figure 15: Failure cases of GPT-4V on *Multiple Chart Understanding* task. RED means the incorrect answers from GPT-4V. BLUE means the manipulated parts of the questions.



Can you convert the chart in the image into a json format?

GPT-4V Output:

```
{"title": "Number of hospitals in Germany from 2000 to 2017",
"years": [2000, 2005, 2010, 2015, 2017],
"values": [4000,3000,2000,1000]
}
```



Question:

Can you convert the chart in the image into a json format?

GPT-4V Output:

{"title": "Total gate revenues from sporting events worldwide by region from 2006 to 2015 (in billion U.S. dollars)",

"years": [2006, 2007, 2008, 2009, 2010, 2011, 2012,

2013, 2014, 2015],

"values": [0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16]}

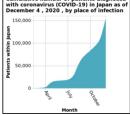
Figure 16: Failure cases of GPT-4V on Chart to Json task. RED means the incorrect answers from GPT-4V.

Prompt:

Here is the description of a chart "Here is a area chart is labeled Cumulative number of patients diagnosed with coronavirus (COVID-19) in Japan as of December 4, 2020, by place of infection. On the x-axis, Month is measured with a categorical scale starting with April and ending with October. There is a linear scale with a minimum of 0 and a maximum of 150,000 along the y-axis, labeled Patients within Japan "

Please generate 3 different questions and answers pairs about title, x-axis, y-axis, data range or data pattern of the chart. The answers should come from the descriptions above. Each Answer must be less than 20 words. The output format should be as follows:

question1=> answer1 => question2=> answer2 => question3=> answer3=>



GPT4 OUTPUT Example:

question1=> What does the area chart represent?

answer1 => Cumulative COVID-19 cases in Japan by place of infection from April to October 2020.

question2=> What does the x-axis represent?

answer2 => Months from April to October 2020

question3=> When did the greatest increase in COVID-19 cases in Japan occur?

answer3=> Between November and December 2020.

Figure 17: An example prompt for text-only GPT4 we use to generate instruction and answers for *Chart Information Extraction* task. The sentence in BLUE is the captions of the chart.

Prompt:

Here is the description of a chart "Here is a area chart is labeled Cumulative number of patients diagnosed with coronavirus (COVID-19) in Japan as of December 4, 2020, by place of infection. On the x-axis, Month is measured with a categorical scale starting with April and ending with October. There is a linear scale with a minimum of 0 and a maximum of 150,000 along the y-axis, labeled Patients within Japan "

Please generate 3 different questions and answers pairs about the trend, data pattern and other insightful analysis of the chart. The answers should come from the descriptions above. Each Answer must be less than 20 words. The output format should be as follows:

question1=>

answer1 =>

question2=>

answer2 =>

question3=>

answer3=>

GPT4 OUTPUT Example:

question1=> When was the first COVID-19 case diagnosed in Japan?

answer1 => March 2020.

question2=> How many COVID-19 cases were reported in Japan by December 4th, 2020?

answer2 => Approximately 160,000.

question3=> When did the greatest increase in COVID-19 cases in Japan occur?

answer3=> Between November and December 2020.

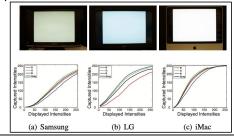
Figure 18: An example prompt for text-only GPT4 we use to generate instruction and answers for *Chart Reasoning* task. The sentence in BLUE is the captions of the chart.

Prompt:

Here is the description of a chart "Displays vary widely in brightness, hue, white balance, contrast and many other parameters that will influence the appearance of light. To affirm this hypothesis, an SLR camera with fixed parameters observes 3 displays and models the CDTF for each one. See Samsung in Fig. 4(a), LG in Fig. 4(b), and iMac 4(c). Although each display is tuned to the same parameters, including contrast and RGB values, each display produces a unique CDTF. Variance of Light Output among Displays. An SLR camera captured a range of grayscale [0,255] intensity values produced by 3 different LCDs. These 3 CDTF curves highlight the dramatic difference in the light emmitance function for different displays, particularly the LG."

Please generate questions and answers pairs about title, data pattern and purpose of the chart. The answers should come from the descriptions above. The output format should be as follows:

question=> answer =>



GPT4 OUTPUT Example:

question=> What's the main purpose of the image?

answer => The main purpose of the graph is to illustrate the variance in light output among displays. This is done by plotting the CDTF curves for three different LCDs: Samsung. LG, and; iMac. The CDTF curve is a function that describes the relationship between the displayed intensity and the emitted light intensity. The shows that the three displays produce significantly different CDTF curves, which indicates that they have different light output characteristics.

Figure 19: An example prompt for text-only GPT4 we use to generate instruction and answers for *Multiple Chart Understanding* task. The sentence in BLUE is the captions of the chart.

Prompt:

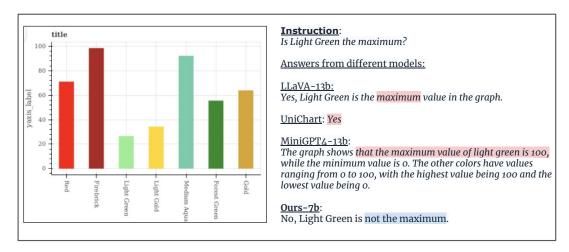
Here is the datatable of a chart "Apparent steel consumption per capita in Mexico from 2003 to 2018 (in kilograms of finished steel products) <s> Year Per capita use in kilograms 2018 194.4 2017 204.8 2016 199.8 2015 197.6 2014 189 2013 167.9 2012* 173.1 2011 166.3 2010 149.7 2009 129.9 2008 154.3 2007 164 2006 158.9 2005 143.9 2004 152.6 2003 144"

Please convert the data table into the json format with the title and data as the key...

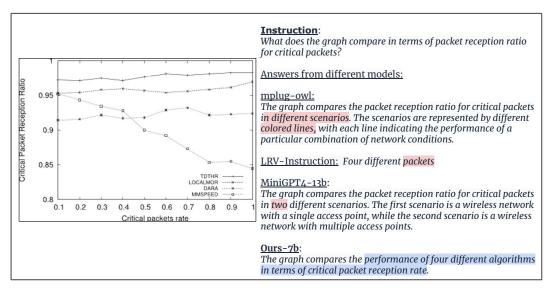
GPT4 OUTPUT Example:

```
{Title: "Apparent steel consumption per capita in Mexico",
Data: [ {"Year": 2018, "Per capita use in kilograms": 194.4},
    {"Year": 2017, "Per capita use in kilograms": 204.8},
    {"Year": 2016, "Per capita use in kilograms": 199.8},
    {"Year": 2015, "Per capita use in kilograms": 197.6},
    {"Year": 2014, "Per capita use in kilograms": 189.0},
    {"Year": 2013, "Per capita use in kilograms": 167.9},
    {"Year": 2012, "Per capita use in kilograms": 173.1},
    {"Year": 2011, "Per capita use in kilograms": 166.3},
    {"Year": 2010, "Per capita use in kilograms": 149.7},
    {"Year": 2009, "Per capita use in kilograms": 129.9},
    {"Year": 2008, "Per capita use in kilograms": 154.3},
    {"Year": 2007, "Per capita use in kilograms": 164.0},
    {"Year": 2006, "Per capita use in kilograms": 158.9},
    {"Year": 2005, "Per capita use in kilograms": 143.9},
    {"Year": 2004, "Per capita use in kilograms": 152.6},
    {"Year": 2003, "Per capita use in kilograms": 144.0}
```

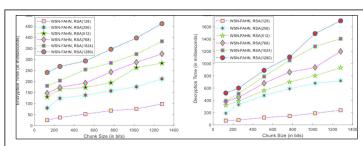
Figure 20: An example prompt for text-only GPT4 we use to generate instruction and answers for *Chart-to-Json* task. The sentence in BLUE is the captions of the chart.



(a) Examples of *Chart Reasoning* task between our model and other open-source models.



(b) Examples of Scientific Chart Understanding task between our model and other open-source models.



Instruction: What is the main takeaway from the graph?

- a) The encryption and decryption times decrease with the increase in key size and chunk size.
- b) The encryption and decryption times remain constant regardless of the increase in key size and chunk size.
- c) The encryption and decryption times increase in all methods with the increase in key size and chunk size.

<u>mplug-owl:</u> The main takeaway from the graph is that the encryption and decryption times decrease with the increase in key size and chunk size.

LRV-Instruction: The encryption and decryption times decrease with the increase in key size and chunk size.

MiniGPT4-13b: The main takeaway from the graph is that the encryption and decryption times decrease with the increase in key size and chunk size.

Ours-7b: The encryption and decryption times increase in all methods with the increase in key size and chunk size.

(c) Examples of Multiple Chart understanding task between our model and other open-source models.

Figure 21: Visualization examples