CHARTMOE: MIXTURE OF DIVERSELY ALIGNED EXPERT CONNECTOR FOR CHART UNDERSTANDING

Zhengzhuo Xu[12*] **Bowen Qu**[13*] **Yiyan Qi**[1*] **Sinan Du**[2] **Chengjin Xu**[1] **Chun Yuan**[2†] **Jian Guo**[14†]
[1]International Digital Economy Academy [2]Tsinghua University [3]Peking University
[4]Hong Kong University of Science and Technology (Guangzhou)
https://github.com/IDEA-FinAI/ChartMoE

ABSTRACT

Automatic chart understanding is crucial for content comprehension and document parsing. Multimodal Large Language Models (MLLMs) have demonstrated remarkable capabilities in chart understanding through domain-specific alignment and fine-tuning. However, current MLLMs still struggle to provide faithful data and reliable analysis only based on charts. To address it, we propose ChartMoE, which employs the Mixture of Expert (MoE) architecture to replace the traditional linear projector to bridge the modality gap. Specifically, we train several linear connectors through distinct alignment tasks, which are utilized as the foundational initialization parameters for different experts. Additionally, we introduce ChartMoE-Align, a dataset with nearly 1 million chart-table-JSON-code quadruples to conduct three alignment tasks (chart-table/JSON/code). Combined with the vanilla connector, we initialize different experts diversely and adopt high-quality knowledge learning to further refine the MoE connector and LLM parameters. Extensive experiments demonstrate the effectiveness of the MoE connector and our initialization strategy, e.g., ChartMoE improves the accuracy of the previous state-of-the-art from 80.48% to 84.64% on the ChartQA benchmark.

1 INTRODUCTION

Charts serve as a fundamental tool for data visualization, with automated chart interpretation gaining prominence in domains such as text analysis Hoque et al. (2017), scientific research Hsu et al. (2021), and policy-making Wu et al. (2024). Chart understanding is a complex task that demands the identification of visual cues, the comprehension of intricate interactions, and the precise inference of values informed by prior knowledge Huang et al. (2024). Previous work Liu et al. (2023b;a) typically pre-trained on domain-specific charts, which are constrained by limited resources and narrow task focus. In contrast, Multi-modal Large Language Models (MLLMs) Li et al. (2023); Liu et al. (2023d); Bai et al. (2023a); Ye et al. (2023b); Chen et al. (2023); OpenAI (2023) exhibit substantial potential in image comprehension and instruction following. The community has achieved advanced progress by creating chart understanding datasets Liu et al. (2023c); Han et al. (2023); Masry et al. (2024b); Xu et al. (2023) and applying supervised fine-tuning based on well-performed MLLMs Meng et al. (2024); Yan et al. (2024). With the exponential growth of chart data, automated chart interpretation via MLLMs is emerging as a promising avenue.

Recent studies advocate for chart alignment as a foundational step for LLaVA-like MLLMs Liu et al. (2023d); Zhang et al. (2023); Xue et al. (2024), which bridge the visual encoder and LLM through MLP connector. They usually utilize chart-to-table alignment task to train the connector effectively Meng et al. (2024); Yan et al. (2024); Hu et al. (2024). However, tables only provide basic information, such as numerical values and titles, which fail to capture the full range of chart elements. Despite some efforts to align with more informative text Yan et al. (2024), the heavy alignment tasks may lead to the erosion of the connector's general capabilities, e.g., instruction following and visual counting, which are derived from the pre-training on large-scale visual-language data. To mitigate knowledge forgetting, one intuitive approach is to further tune with its original data, which results in redundant training and computational burden.

In this paper, we try to address these challenges via Mixture of Experts (MoE) architecture Zoph et al. (2022). MoE enhances model capacity by activating a subset of experts through a router. Since

[*] Equal contributions. [†] Corresponding authors.

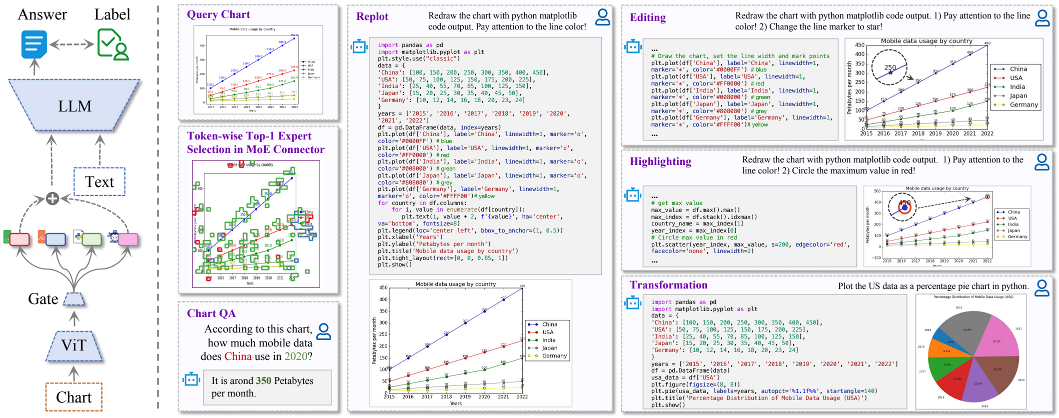

Answer
Label
LLM
Text
Gate
ViT
Chart
Query Chart
Mobile data usage by country
Token-wise Top-1 Expert Selection in MoE Connector
Chart QA
Replot
Editing
Highlighting
Transformation
Mobile data usage by country
Petabytes per month
Years
China
USA
India
Japan
Germany
250
450
Percentage Distribution of Mobile Data Usage (USA)

Chart QA

According to this chart, how much mobile data does China use in 2020?

It is arond 350 Petabytes per month.

Replot

Redraw the chart with python matplotlib code output. Pay attention to the line color!

```
import pandas as pd
import matplotlib.pyplot as plt
plt.style.use("classic")
data = {
'China': [100, 150, 200, 250, 300, 350, 400, 450],
'USA': [50, 75, 100, 125, 150, 175, 200, 225],
'India': [25, 40, 55, 70, 85, 100, 125, 150],
'Japan': [15, 20, 25, 30, 35, 40, 45, 50],
'Germany': [10, 12, 14, 16, 18, 20, 23, 24]
}
years = ['2015', '2016', '2017', '2018', '2019', '2020',
'2021', '2022']
df = pd.DataFrame(data, index=years)
plt.plot(df['China'], label='China', linewidth=1, marker='o',
color='#0000FF') # blue
plt.plot(df['USA'], label='USA', linewidth=1, marker='o',
color='#FF0000') # red
plt.plot(df['India'], label='India', linewidth=1, marker='o',
color='#008000') # green
plt.plot(df['Japan'], label='Japan', linewidth=1, marker='o',
color='#808080') # grey
plt.plot(df['Germany'], label='Germany', linewidth=1,
marker='o', color='#FFFF00')# yellow
for country in df.columns:
    for i, value in enumerate(df[country]):
       plt.text(i, value + 2, f'{value}', ha='center',
va='bottom', fontsize=8)
plt.legend(loc='center left', bbox_to_anchor=(1, 0.5))
plt.xlabel('Years')
plt.ylabel('Petabytes per month')
plt.title('Mobile data usage by country')
plt.tight_layout(rect=[0, 0, 0.85, 1])
plt.show()
```

Editing

Redraw the chart with python matplotlib code output. 1) Pay attention to the line color! 2) Change the line marker to star!

```
...
# Draw the chart, set the line width and mark points
plt.plot(df['China'], label='China', linewidth=1,
marker='*', color='#0000FF') # blue
plt.plot(df['USA'], label='USA', linewidth=1,
marker='*', color='#FF0000') # red
plt.plot(df['India'], label='India', linewidth=1,
marker='*', color='#008000') # green
plt.plot(df['Japan'], label='Japan', linewidth=1,
marker='*', color='#808080') # grey
plt.plot(df['Germany'], label='Germany', linewidth=1,
marker='*', color='#FFFF00')# yellow
...
```

Highlighting

Redraw the chart with python matplotlib code output. 1) Pay attention to the line color! 2) Circle the maximum value in red!

```
...
# get max value
max_value = df.max().max()
max_index = df.stack().idxmax()
country_name = max_index[1]
year_index = max_index[0]
# Circle max value in red
plt.scatter(year_index, max_value, s=200, edgecolor='red',
facecolor='none', linewidth=2)
...
```

Transformation

Plot the US data as a percentage pie chart in python.

```
import pandas as pd
import matplotlib.pyplot as plt
data = {
'China': [100, 150, 200, 250, 300, 350, 400, 450],
'USA': [50, 75, 100, 125, 150, 175, 200, 225],
'India': [25, 40, 55, 70, 85, 100, 125, 150],
'Japan': [15, 20, 25, 30, 35, 40, 45, 50],
'Germany': [10, 12, 14, 16, 18, 20, 23, 24]
}
years = ['2015', '2016', '2017', '2018', '2019', '2020', '2021', '2022']
df = pd.DataFrame(data)
usa_data = df['USA']
plt.figure(figsize=(8, 8))
plt.pie(usa_data, labels=years, autopct='%1.1f%%', startangle=140)
plt.title('Percentage Distribution of Mobile Data Usage (USA)')
plt.show()
```

Figure 1: Overview and capabilities of ChartMoE: We introduce a MoE architecture connector and provide visualizations of the top-1 expert selection (refer to Fig. 6 and Appendix B for details). ChartMoE can extract highly precise values and provide flexible chart editing through code-based interactions.

the alignment tasks work on the connector, we replace only the MLP projector with MoE while keeping the vision encoder and LLM frozen. Our insight lies in the ***expert initialization manner***. Random initialization can lead to training instability and convergence at sub-optimal points (Fig. 4). Recent co-upcycling initialization Komatsuzaki et al. (2023) addresses this issue by duplicating the vanilla connector parameters across all experts. However, it fails to avoid the dilemma of expert homogenization, where the experts end up with similar functionalities.

In contrast, we attempt to inject distinct prior knowledge into each expert first to tackle these challenges. Unlike natural images, *charts can be represented in various text formats, e.g., tables, attribute JSON, and rendering code*. As shown in Fig. 1& 2, in addition to chart-table, we introduce chart-JSON alignment to capture detailed elements like color or topological relationships and chart-code alignment to incorporate rendering details such as numerical values, color hex codes, and visual elements interactions (refer to Appendix C). We independently conduct various alignment tasks to capture more diverse chart features and thus obtain three distinct initialization approaches. We also retain the vanilla connector to preserve the capabilities of the MLLM on general tasks effectively.

Building upon the proposed four initialization manners, we introduce ChartMoE, an SFT-based MLLM with MoE connector for chart comprehension and reasoning. Our purpose in applying MoE connector is not to increase model capacity, but rather to improve chart comprehension and diverse representation through alignment tasks, while maintaining performance on other general tasks. Hence, we preserve the original connector parameters as one expert initialization manner. The MoE connector is extremely lightweight, so it adds negligible computational cost during both training and inference. Interestingly, we observe that experts in ChartMoE exhibit distinct visual token preferences, e.g., the vanilla expert favors background tokens while other experts focus more on tokens with legends or numbers (Fig. 6 and Appendix B). Considering that the distribution of visual tokens is naturally imbalanced in chart scenarios, we remove the expert-balanced loss in MoE and obtain further performance gain. Due to the scarcity of rich structural text for chart alignment, we design a pipeline (Fig. 3) to generate nearly 1 million quadruplets chart-table-JSON-code to build the ChartMoE-Align dataset for alignment. We train ChartMoE in 3 stages. First, we initialize experts via the proposed four manners. Then, we conduct high-quality knowledge learning using the MMC instruction Liu et al. (2023c) to train the routing network, expert connectors, and LoRA Hu et al. (2022) modules. Finally, we employ annealing training on ChartQA Masry et al. (2022) and ChartGemma Masry et al. (2024b). ChartMoE achieves state-of-the-art (SOTA) performance and provides more precise numbers and comprehensive attributes of charts (Appendix E). Refer to Appendix D.1 for detailed comparisons with other MoE works w.r.t. *motivation*, *initialization*, and *complexity*. In summary, our contributions are:

a) We present ChartMoE for faithful and reasonable chart understanding, with the connector based on Mixture of Expert architecture, to bridge the chart and LLM branches. All experts are initialized based on various alignment training tasks to avoid expert homogenization.

b) We introduce ChartMoE-Align, a large-scale dataset with nearly 1 million meticulous chart-table-JSON-code quadruplets for chart alignment pre-training.

c) We propose to train ChartMoE with a three-stage training paradigm, including connector alignment pre-training, high-quality knowledge learning, and annealing chart tuning.

d) Extensive quantitative and qualitative studies demonstrate that ChartMoE significantly outperforms previous state-of-the-art across several benchmarks by a large margin.

2 Related Work

Multimodal large language models leverages a connector to bridge the gap between large language models Touvron et al. (2023); Radford et al. (2018); Brown et al. (2020); Zhang et al. (2022); Zheng et al. (2023) and vision encoders Radford et al. (2021); Oquab et al. (2023) to enable enriched capabilities of comprehension and instruction following. Approaches such as BLIP2 Li et al. (2023), Flamingo Alayrac et al. (2022), mPLUG-Owl Ye et al. (2023b), and Qwen-VL Bai et al. (2023b) utilize QFormers or Resamplers to align modalities on extensive datasets of image-text pairs. LLaVA Liu et al. (2023d; 2024b) is the pioneering work to extend the instruction tuning paradigm to visual tasks with text-only GPT-4 OpenAI (2023), achieving tremendous performance using a simple MLP without compromising visual information to refine the multimodal alignment. Some works Lin et al. (2023); Tong et al. (2024b;a) explore the combination of various vision encoders, complementarily enhancing visual representations to bolster the fine-grained visual perception of MLLMs. Despite efforts in structural design, training strategies and data quality remain crucial in the advancement of MLLMs.

Chart Reasoning refers to chart analysis, summarization, and etc. Existing methods can be categorized as 1) *Two-stage methods* use specialized extraction modules to generate intermediary representations of chart information, like tables, which are provided as textual prompts for LLMs. Pix2Struct Lee et al. (2023) aligns markdown data with charts. MatCha Liu et al. (2023b) aligns various data formats (e.g., tables and code) with charts on several downstream tasks. DePlot Liu et al. (2023a) fine-tunes Pix2Struct for table extraction and uses LLMs to process queries based on the extracted data. ChartVLM Xia et al. (2024) employs a discriminator to ascertain the necessity of intervention by LLMs for a given query. 2) *End-to-end methods* strive to tackle chart reasoning challenges with a unified model. ChartLlama Han et al. (2023) incorporates diverse charts and downstream tasks based on LLaVA Liu et al. (2023d). ChartPaLI Carbune et al. (2024), ChartAst Meng et al. (2024), and MMC Liu et al. (2023c) conduct alignment on table-chart pairs. UReader Ye et al. (2023a) aligns all data with markdown, while mPLUG-Owl2 Ye et al. (2023c) achieves superior performance with high-resolution inputs. ChartThinker Liu et al. (2024c) and DOMINO Wang et al. (2023) propose the CoT Wei et al. (2022) for chart reasoning. LaMenDa Zhuowan et al. (2024) trains MLLMs via step-by-step reasoning QA. ChartReformer Yan et al. (2024) introduces chart-JSON alignment, while OneChart Chen et al. (2024) aligns charts with Python dictionaries. MiniGPT-v2 Chen et al. (2023), Doc-Owl Hu et al. (2024), and TinyChart Zhang et al. (2024) tackle the reasoning efficiency for high-resolution charts by merging tokens.

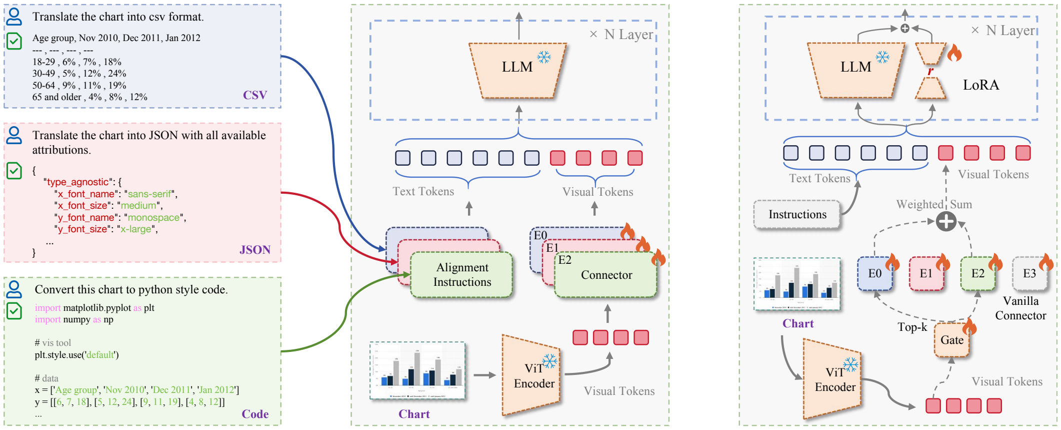
3 ChartMoE

3.1 Architecture

The ChartMoE is based on InternlmXC-v2 Dong et al. (2024) due to the concise LLaVA-like architecture Liu et al. (2023d) and performance on par with GPT-4 on text-image comprehension. The base model includes a vision encoder and a LLM connected by a two-layer MLP. ChartMoE replaces the MLP with a MoE architecture as the connector to leverage diverse prior knowledge.

Vision Encoder. We utilize CLIP ViT-Large Radford et al. (2021) as the vision encoder, leveraging its rich prior knowledge gained from training on millions of image-text pairs. Considering the impact of chart resolution on performance, we set the input resolution to 490 × 490 to strike a balance between efficiency and performance. Formally, the visual encoder $\mathcal{M}^V(\cdot)$ will project the chart $\mathcal{I}$ into N tokens $V := \{v_1, v_2, \ldots, v_N\}$, where $N = 1225$ in the ChartMoE.

Mixture-of-Experts Connector. As illustrated in Fig. 2c, the MoE architecture employs a parallel multi-expert collaboration approach. This architecture comprises L experts $\mathcal{M}^E(\cdot)$, each designed with the same linear layer as the baseline. For a visual token v_i given by $\mathcal{M}^V$, the gating network $\mathcal{M}^G(\cdot)$ will calculate the routing weight $g_j(v_i)$ of each expert $\mathcal{M}^E_j(\cdot)$ and select top-K to activate.



Translate the chart into csv format.

```
Age group, Nov 2010, Dec 2011, Jan 2012
--- , --- , --- , ---
18-29 , 6% , 7% , 18%
30-49 , 5% , 12% , 24%
50-64 , 9% , 11% , 19%
65 and older , 4% , 8% , 12%
```

Translate the chart into JSON with all available attributions.

```
{
   "type_agnostic": {
      "x_font_name": "sans-serif",
      "x_font_size": "medium",
      "y_font_name": "monospace",
      "y_font_size": "x-large",
    ...
}
```

Convert this chart to python style code.

```
import matplotlib.pyplot as plt
import numpy as np

# vis tool
plt.style.use('default')

# data
x = ['Age group', 'Nov 2010', 'Dec 2011', 'Jan 2012']
y = [[6, 7, 18], [5, 12, 24], [9, 11, 19], [4, 8, 12]]
...
```

(a) Alignment Instructions (b) Alignment Pretraining (c) Supervised Finetuning

Figure 2: Overview of proposed ChartMoE. (a) Examples of alignment instructions. (b) We conduct three different alignment tasks in parallel. (c) We initialize MoE connectors in four different manners and train the gate network, experts, and LoRA during the supervised fine-tuning stage.

Finally, the tokens processed by each expert $\mathcal{M}_j^E$ will be averaged according to the weight $g_j(v_i)$ given by $\mathcal{M}^G$ to get the token $\hat{v}_i$ for the LLM branch $\mathcal{M}^L$.

Large Language Model. Following the baseline, we employ the *InternLM2-7B-ChatSFT* variant as the LLM $\mathcal{M}^L$, implemented as a transformer decoder with a causal attention mask. We concate the visual tokens $\hat{V} := \{\hat{v}_1, \hat{v}_2, \dots, \hat{v}_N\}$ given by MoE connector with the M input text $\mathcal{T}$ tokens $T := \{t_1, t_2, \dots, t_M\}$ to form the input token sequence for the LLM $\mathcal{M}^L$. Formally, given the chart $\mathcal{I}$ and instruction $\mathcal{T}$, the output $\mathcal{O}$ of proposed ChartMoE can be formulated as:

$$\{v_1, v_2, \dots, v_N\} = \mathcal{M}^V(\mathcal{I}), \tag{1}$$

$$\hat{v}_i = \sum_j^L g_j(v_i)\mathcal{M}_j^E(v_i), \quad g(v_i) = \text{Top}(\sigma(\mathcal{M}^G(v_i)); K), \tag{2}$$

$$\mathcal{O} = \mathcal{M}^L(\{\hat{v}_1, \hat{v}_2, \dots, \hat{v}_N; t_1, t_2, \dots, t_M\}), \tag{3}$$

where σ indicates *softmax* and the $\text{Top}(\cdot; K)$ will reset the non-Top K routing weight to 0.

Initialization of Expert. Previous approaches initialize expert parameters via *1) Random initialization*, which may lead to convergence difficulties during supervised fine-tuning, and *2) Co-upcycling initialization* Komatsuzaki et al. (2023), i.e., copy baseline connector parameters to each expert, which may lead to homogenization of experts. ChartMoE proposes initializing experts' parameters through distinct alignment tasks. We eliminate the load-balancing loss typically used in standard MoE architectures to equalize expert activation frequencies, as our initialization approach allows each expert to specialize in its preferred visual tokens, which inherently exhibit biased distributions.

3.2 Alignment Pre-training.

The key insight of ChartMoE is the experts' initialization parameters from the different alignment pre-training (Fig. 2a). Specifically, as illustrated in Fig. 2b, we align expert connectors using three distinct alignment tasks, where only the connector parameters will be updated. We visualize the *visual token preferences* of each expert for both chart (Fig. 6& 12) and non-chart (Fig. 11) images.

Alignment with Table. Charts convey key information that can be more precisely expressed in tabular form, and LLMs are particularly adept at processing such structured data. Hence, we introduce a chart-table alignment task, aiming to translate chart content into tabular format. The connector is trained to convert chart information into corresponding CSV tables, thereby improving model performance in numerical data extraction and chart interpretation.

Alignment with JSON. Although tables capture the numerical information from charts, they miss semantic details such as colors, shapes, and fonts. To fill this gap, we propose a chart-JSON alignment task, which represents chart attributes in JSON format. This task requires the connector to

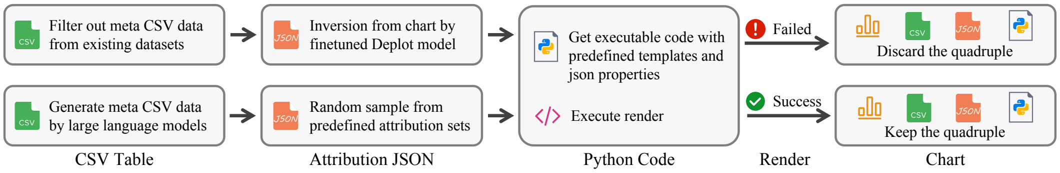

Filter out meta CSV data from existing datasets
Generate meta CSV data by large language models
Inversion from chart by finetuned Deplot model
Random sample from predefined attribution sets
Get executable code with predefined templates and json properties
Execute render
Failed
Success
Discard the quadruple
Keep the quadruple
CSV Table
Attribution JSON
Python Code
Render
Chart

Figure 3: Overview of ChartMoE-Align data generation pipeline. The charts are plotted by Python *matplotlib*.

focus not only on the numerical data but also on visual and semantic properties. Accurately extracting chart attributes is essential for tasks like chart redrawing and editing.

Alignment with Code. To fully align with charts, we further introduce a chart-code alignment task. Since the underlying drawing code fully defines a chart, this approach enables the connector to convert the chart's visual tokens into representations in the LLM domain. Notably, we provide the drawing code explicitly, including precise numerical values and rendering attributes, e.g., numbers represented in Python lists and colors in hexadecimal code. Refer to Fig. 13 for more detailed cases. The code enables the model to perform in-depth summarization, analysis, and editing of charts. This expert is significantly more sensitive to the trends and key elements in the charts.

Table 1: Datasets used for training ChartMoE. We conduct alignment pre-training with synthetic data and supervised tuning with high-quality, real-world data. Only ChartQA is used in the ablation due to GPU constraints.

Source	Data Type	Task Type	Samples
		Alignment Training	

ChartQA	synthetic	`chart` to `table`
		`chart` to `JSON`
		`chart` to `code`
			18.3K
			18.3K
			18.3K

PlotQA	synthetic	`chart` to `table`
		`chart` to `JSON`
		`chart` to `code`
			157K
			157K
			157K

ChartY	synthetic	`chart` to `table`
		`chart` to `JSON`
		`chart` to `code`
			763.6K
			763.6K
			763.6K

Total Usage: `Table` = 500K `JSON` = 200K `Code` = 100K			2.8M 800K
		High-Quality Knowledge Learning	
MMC	synthetic & real world	QA & reasoning & summariztion	410K
		Chart Specific Annealing Tuning	
ChartQA	real world	QA	28.3K×2
ChartGemma	real world	QA & PoT & reasoning & summariztion	163.2K
Total			220.8K

ChartMoE-Align generation pipeline. As Fig. 3 illustrates, 1) We filter charts with meta CSV from existing datasets Masry et al. (2022); Methani et al. (2020) and data generated by LLMs Chen et al. (2024). 2) We use a fine-tuned Deplot Liu et al. (2023a) to inverse the plotting attributes following the templates provided by ChartReformer and randomly sample missing attributes from the predefined set. 3) We create code templates for different types of charts and generate plotting code based on the meta CSV and extracted JSON attributes. *Note that all values and attributes in the code are explicitly represented.* 4) We retain the `(table, JSON, code, chart)` quadruples that pass compilation. Tab. 1 shows the data sources & size and refer to Appendix C for details.

3.3 Supervised Fine-tuning.

We initialize ChartMoE using the structure shown in Fig. 2c after aligning the connectors across 3 distinct tasks separately. We also retain the vanilla connector to maintain the baseline's excellent dialogue capabilities, which aligns with the principle of residual optimization He et al. (2016). We train the MoE connector and LLM during this stage with LoRA Hu et al. (2022), as shown in Fig. 2c. Considering the training principles proposed in LLaVA-NeXT Liu et al. (2024a), this stage is divided into high-quality knowledge learning and chart-specific annealing training.

High-Quality Knowledge Learning. We adopt MMC Liu et al. (2023c) to enhance the ChartMoE's knowledge. MMC includes a variety of chart types and tasks such as chart-related question answering, translation, extraction, reasoning, and analysis. Considering data quality, we only utilize the MMC-Instruction subset, which has been manually verified. Notice that the quality of instruction data is more important than quantity in this stage.

Chart Specific Annealing Tuning. Following Llama-v3.1 Team et al. (2024b), we perform annealing tuning before evaluating mainstream benchmarks. We increase the learning rate and conduct instruction tuning using the training sets of ChartQA and ChartGemma to adjust the query styles and answer formats of these benchmarks.

Program of Thought (PoT) Inference. We require the model to generate the variables and operation code rather than producing direct answers. This inference pipeline addresses the mathematical capabilities by employing *Python* to handle the logical computations, which is the shortcoming of

Table 2: The relaxed accuracy (%) performance on ***ChartQA***. Ada.: Adaptive input resolution. *: Multi-scale image feature, 448×448 in DocOwl. †: Employing token merging to reduce computational overhead.

Models	Para.	Resolution	Relax Acc. @0.05			Relax Acc. @0.10			Relax Acc. @0.20		
			Human	Aug.	Avg.	Human	Aug.	Avg.	Human	Aug.	Avg.
General MLLMs											
LLaVA-v1.5	13B	@336	25.36	18.56	21.96	28.56	23.52	26.04	32.56	30.72	31.64
Qwen-VL	9.6B	@448	40.48	79.76	60.12	43.20	82.56	62.88	47.52	85.76	66.64
DocOwl-v1.5	8B	@448*	47.44	91.52	69.48	51.92	92.08	72.00	56.72	93.12	74.92
InternlmXC-v2	8B	@490	62.72	81.28	72.00	66.72	84.08	75.40	70.80	86.56	78.68
Specialist Chart Models											
Pix2Struct	282M	Ada.	30.08	76.88	53.48	31.68	78.40	55.04	37.28	81.12	59.20
Matcha	282M	Ada.	37.12	86.64	61.88	39.84	87.36	63.60	43.52	88.56	66.04
UniChart	201M	@960	34.64	83.28	58.96	36.48	84.24	60.36	38.88	85.28	62.08
Deplot + LLaVA-v1.6	282M+13B	Ada.	53.44	87.68	70.56	56.80	88.48	72.64	60.64	90.08	75.36
Chart MLLMs											
ChartVLM	13B	Ada.	42.08	82.48	62.28	43.84	82.88	63.36	46.00	83.28	64.64
OneChart	125M+13B	@1024	54.48	87.12	70.80	57.60	87.84	72.72	62.00	88.64	75.32
ChartLlama	13B	@336	58.40	93.12	75.76	61.20	93.60	77.40	63.52	94.00	78.76
ChartGemma+PoT	3B	@448	67.84	85.28	76.56	68.64	85.84	77.24	69.84	86.32	78.08
TinyChart	3B	@768†	58.72	**94.88**	76.80	62.56	**95.28**	78.92	67.04	**96.16**	81.60
ChartAst	13B	@448	64.88	93.12	79.00	66.24	93.84	80.04	67.44	94.32	80.88
TinyChart+PoT	3B	@768†	70.24	90.72	80.48	71.20	91.44	81.32	72.40	92.56	82.48
ChartMoE (Ours)	8B	@490	71.36	91.04	81.20	75.12	92.48	83.80	78.16	93.68	85.92
ChartMoE+PoT (Ours)	8B	@490	**78.32**	90.96	**84.64**	**80.16**	92.32	**86.24**	**82.08**	93.60	**87.84**

all open-sourced models. With better numerical extraction abilities, PoT can significantly enhance our ChartMoE's question-answering performance.

4 Experiment

4.1 Implementation Details

During the alignment stage, we train the connector parameters and keep the visual encoder and LLM parameters frozen. In the supervised fine-tuning stage, we continue training the MoE connector while employing LoRA to update the LLM parameters. All training processes are conducted on 4 × A100-40G GPUs. You can refer to Appendix A.2 for more details.

4.2 Evaluation Metrics

ChartQA Masry et al. (2022) test split consists of 1,250 questions in both human and augmented parts. The charts are three common chart types and are sourced from the real world. It features a variety of human-crafted questions and answers to evaluate models' understanding, reasoning, and data extraction skills. ChartQA adopts relaxed accuracy, which is highlighted shortcomings by recent studies Chen et al. (2024); Xu et al. (2023), such as simplistic string matching and direct float conversion. Therefore, we improve it by 1) using regular expression matching to extract number values, 2) optimizing string matching for short answers, and 3) demonstrating model performance under various relaxed margins. We adopt it for all experiment results.

ChartBench Xu et al. (2023) focuses on charts without data point annotations. It includes a broader range of chart types, with 9 main categories and 42 subcategories, each containing 50 charts. ChartBench focuses on extracting numerical values, posing a greater challenge as models cannot depend on OCR for precise answers. It adopts *Acc+* for judgments and relaxed accuracy for NQA tasks. The benchmark proposes to extract number values by LLMs first, which is omitted for the stratifying instruction-following ability of ChartMoE.

ChartFC Akhtar et al. (2023a) & **ChartCheck** Akhtar et al. (2023b) adopt accuracy to verify whether the claim aligns with the input chart, marking a significant advancement in chart recognition and reasoning abilities. This identifies the potential hallucinations in chart-related contexts. The ChartFC test set has 1,591 questions, and the ChartCheck test set has two splits, containing 937 questions and 981 questions.

4.3 Comparative Models

General MLLMs. We compare PaliGemma Beyer et al. (2024), LLaVA-v1.5 Liu et al. (2023d) with an MLP connector, Qwen-VL Bai et al. (2023b) with a Qformer Li et al. (2023) connector, DocOwl-

Table 3: The zero-shot performance on ***ChartBench***. No methods are fine-tuned on the trainset for fairness. We exclude PoT because ChartBench mainly assesses numerical extraction accuracy without math calculation.

Models	Regular Type				Extra Type							ALL
	Line	Bar	Pie	Avg.	Area	Box	Radar	Scatter	Node	Comb.	Avg.	
General MLLMs												
LLaVA-v1.5	29.12	21.26	17.28	22.10	21.73	20.94	27.50	23.47	36.80	24.30	24.96	23.38
Qwen-VL	38.00	20.71	38.24	29.46	28.83	24.17	35.00	19.50	18.50	25.50	26.56	28.18
DocOwl-v1.5	49.60	31.69	31.54	35.68	12.27	23.33	22.50	36.13	29.60	38.80	27.38	32.05
Mini-Gemini	34.88	36.12	40.40	36.77	31.20	23.33	30.60	35.20	43.60	27.90	30.61	34.37
InternlmXC-v2	68.16	48.74	**56.60**	54.50	27.47	**25.33**	40.10	52.93	50.40	46.20	39.72	48.41
Specialist Chart Models												
Pix2Struct	2.56	2.37	1.90	2.33	0.13	0.13	4.60	0.67	0.40	3.20	2.93	2.16
Matcha	6.80	5.05	3.60	5.18	0.27	1.60	6.20	3.46	5.40	4.80	5.81	4.84
UniChart	7.04	5.35	4.30	5.55	3.86	4.80	11.60	5.06	15.80	9.60	8.30	6.78
Deplot+LLaVA-v1.6	31.20	26.46	24.00	27.09	21.34	13.34	24.00	41.34	42.00	31.00	31.57	27.62
Chart MLLMs												
ChartVLM	21.92	14.16	10.50	15.16	7.47	7.87	8.00	7.87	5.40	10.50	8.38	11.96
ChartLlama	26.80	18.83	20.80	20.99	14.27	12.00	24.30	27.73	26.20	25.80	21.71	21.31
TinyChart	32.40	25.81	22.50	26.71	10.13	14.80	13.40	28.14	10.80	21.60	22.56	22.51
OneChart	41.28	30.28	29.60	32.65	19.07	13.20	24.60	38.53	34.80	27.90	31.91	29.93
ChartGemma	50.48	38.21	32.10	39.89	28.27	24.13	28.10	48.00	41.80	43.40	42.47	38.46
ChartMoE (Ours)	**71.44**	**51.57**	52.80	**56.31**	**38.40**	24.13	**40.20**	**62.67**	**58.00**	**49.20**	**55.58**	**51.67**

v1.5 Hu et al. (2024) that employs multi-level image resolution and token convolution techniques, and the current open-source SOTA, InternlmXC-v2 Dong et al. (2024).

Specialist Chart Models. Previous works specifically design models and algorithms for chart question answering. We compare Pix2Struct Lee et al. (2023), Matcha Liu et al. (2023b), UniChart Masry et al. (2023), and Deplot Liu et al. (2023a). Notably, Deplot fails to handle questions in arbitrary formats, so we extract table information with Deplot and use LLaVA-v1.6 to answer the questions.

Chart MLLMs. Chart-oriented MLLMs are the promising direction for utilizing prior knowledge of LLMs. ChartLLaMA Han et al. (2023) proposes to generate high-quality instruction data to improve chart question-answering capabilities. ChartAst Meng et al. (2024) suggests aligning the connector with chart-table pairs before supervised fine-tuning. ChartVLM Xia et al. (2024) uses different decoders to handle different questions based on their difficulty. ChartInstruct Masry et al. (2024a) conducts large-scale chart instruction tuning based on general MLLMs. OneChart Chen et al. (2024) converts the chart to the table with a dedicated decoder and uses LLMs to answer questions. ChartGemma Masry et al. (2024b) proposes more instruction data and achieves efficient chart reasoning based on SigLIP Zhai et al. (2023) and Gemma-2B Team et al. (2024a). TinyChart Zhang et al. (2024) adopts token merge to reduce visual tokens and enable high-resolution chart input.

4.4 Main Results

ChartQA. Tab.2 presents detailed comparisons of ChartMoE on ChartQA. ChartMoE significantly improves the baseline (InternlmXC-v2) performance (72.00% vs. 84.64%, +12.64%↑ in Acc.@0.05). Compared to previous SOTA (TinyChart+PoT @768 pixel), ChartMoE consistently surpasses it across all metrics. The PoT effectively enhances the mathematical reasoning capabilities, which is a common shortfall in current MLLMs. ChartMoE integrates better with PoT, indicating that it accurately extracts fundamental elements from charts. ChartMoE shows more significant improvement on *Human* part, especially after incorporating PoT, where the questions are more computationally complex and challenging. Notably, our error analysis in the *Augmented* part reveals that many errors stem from limitations of the evaluation criteria, i.e., string matching. For instance, it is marked incorrect if the prediction is *It is between 2003 and 2005* and the ground truth is *(2003, 2005)*. Forcing performance improvement may lead to model overfitting.

ChartBench. Tab. 3 presents detailed comparisons of ChartMoE on ChartBench. None of the models, including our ChartMoE, undergo supervised fine-tuning on the ChartBench trainset to ensure fair experimental comparison. Chart-specific models typically underperform due to limited generalization, which fails to manage the annotated charts effectively ($< 10\%$). Deplot shows a distinct advantage over these types of models (27.62%) with the assistance of LLaVA-v1.6. The baseline (InternlmXC-v2) demonstrates strong generalization on ChartBench (48.41%), which may benefit from pre-training instructions designed for unannotated charts. Without additional design, ChartMoE improves the baseline performance comprehensively (48.41% vs. 51.67%), especially on extra chart types (39.72% vs. 55.58%, +15.86%↑).

ChartFC & ChartCheck. Tab. 4 compares ChartMoE on the synthetic ChartFC and real-world ChartCheck. ChartMoE consistently outperforms SOTA (e.g., ChartGemma +4.4%↑ on ChartFC) and significantly improves the performance compared to InternlmXC-v2 (+6.83%↑ and +8.76%↑ on ChartCheck T1 and T2, respectively). Note that this is implemented without using training data for supervised fine-tuning, demonstrating ChartMoE's strong generalization capabilities.

Models	ChartFC	ChartCheck	
		T1	T2
PaliGemma	58.26	67.34	68.50
LLaVA-v1.5†	61.28	70.22	70.03
InternlmXC-v2	65.93	72.04	70.44
ChartInstruct-LLama2	69.57	70.11	68.80
ChartInstruct-FlanT5XL	70.27	72.03	73.80
ChartGemma	70.33	71.50	74.31
ChartMoE (Ours)	**74.73**	**78.87**	**79.20**

Table 4: The accuracy performance on ***ChartFC*** and ***ChartCheck***. †: tuning with ChartGemma instructions.

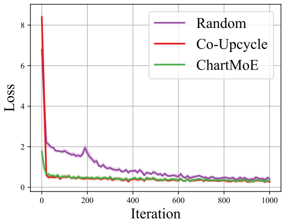


Figure 4: Training loss of different initialization.

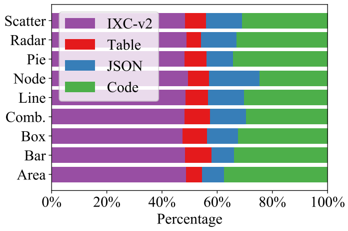


Figure 5: Top-2 selected expert distribution on ChartBench.

5 Further Study

5.1 Model Architecture Ablation

We investigate the impact of three factors on our MoE connector: the number of experts, the number of activated experts, and the expert initialization manner. All the experiments are conducted with ChartQA training data and evaluated on ChartQA test split with relax accuracy metric.

Effect of the Expert Initialization Manner. The initialization strategy plays a crucial role in determining the performance of the MoE connector. Effective initialization is essential to ensure that each expert performs its designated function optimally. As illustrated in Tab. 5 row 1-3, we explore the impact of 3 initialization strategies for the MoE connector. Random initialization serves as a baseline but struggles with convergence (refer to Fig. 4), resulting in a suboptimal accuracy of 73.20% at Acc.@0.05. Following CuMo Li et al. (2024), we employ the Co-Upcycle strategy by replicating the *table-JSON-code* aligned connector for all experts. Given the same starting point, this approach lacks expert diversity, which limits its effectiveness, resulting in an accuracy of 77.48% at Acc.@0.05. In contrast, our initialization assigns distinct parameters to each expert. This tailored approach enables each expert to capitalize on its specific strengths, resulting in the highest performance, achieving 78.76% in Acc.@0.05.

Effect of Number of Experts and Activated Experts. As shown in rows 3-4 of Tab. 5, we compare ChartMoE configurations with 4 and 8 experts, keeping 2 experts activated. The 8 experts are initialized in pairs using the 4 methods illustrated in Fig. 2c. ChartMoE achieves 78.76% in Acc.@0.05 with 4 experts, which is slightly higher than the 78.60% achieved with 8 experts, showing a marginal increase of +0.16%. In rows 4-5, we compare the performance of configurations with 2 and 4 activated experts, finding similar results: 78.60% vs. 78.64% in Acc.@0.05. This analysis suggests that merely increasing the number of experts or the activation of experts does not guarantee improved performance. The configuration with 4 experts and 2 activated experts effectively balances complexity and performance, making it a suitable choice for ChartMoE.

5.2 Training Strategy Ablation

We analyze the impact of the training strategy across alignment and supervised fine-tuning stages. We use InternlmXC-v2 with ChartQA fine-tuning as our baseline, maintaining the same hyperparameters as the chart-specific annealing tuning stage.

Effect of Alignment Strategy. As shown in rows 1-3 of Tab. 6, translating the chart image into structural text formats such as table, JSON, and code during the alignment stage significantly enhances performance in downstream chart understanding tasks. After applying *table-JSON-code* alignment, the model achieves 77.20% in Acc.@0.05, representing a notable improvement

Table 5: Ablation study on ChartMoE architecture w.r.t. the total / activated / initialization of connector experts. All experiments are conducted on ChartQA.

Total Experts	Activated Experts	Experts Initialization	Relax Acc @0.05		
			Human	Aug.	Avg.
4	2	Random Init.	59.68	86.72	73.20
4	2	Random Align	62.32	88.88	75.60
4	2	Co-Upcycle Init.	64.96	90.00	77.48
4	2	Diversely Align	**67.92**	89.60	**78.76**
8	2	Diversely Align	67.20	**90.00**	78.60
8	4	Diversely Align	67.68	89.60	78.64

Table 6: Ablation study on the proposed training strategy and connector architecture on the alignment, high-quality knowledge learning, and chart-specific anneal tuning stages.

ChartMoE Recipe	Relax Acc @0.05		
	Human	Aug.	Avg.
Baseline: InternlmXC-v2 + ChartQA	63.68	87.68	75.68
+ *table-JSON-code* Aligned Connector	64.24	90.16	77.20
+ *Top2-in-4* ChartMoE Connector	67.92	89.60	78.76
+ *MMC* High-Quality Knowledge Learning	67.84	90.24	79.04
+ *ChartGemma* Instructions	**71.36**	**91.04**	**81.20**

Table 7: Ablation study on the expert of MoE connector. We ignore the gating network and adopt specific expert output.

Connector	Relax Acc @0.05		
	Human	Aug.	Avg.
Expert 0 (Vanilla)	**69.76**	**89.84**	**79.80**
Expert 1 (Table)	63.60	89.12	76.36
Expert 2 (JSON)	60.64	82.48	71.56
Expert 3 (Code)	<u>66.88</u>	<u>89.36</u>	<u>78.12</u>

Table 8: Ablation study on alignment pre-training tasks. We adopt different alignment tasks for baseline (linear connector) and further conduct supervised fine-tuning on the ChartQA train set.

Alignment	*w/o* ChartQA SFT			*w/i* ChartQA SFT		
	Human	Aug.	Avg.	Human	Aug.	Avg.
Vanilla	**62.72**	**81.28**	**72.00**	63.68	87.68	75.68
Table	<u>51.28</u>	<u>71.76</u>	<u>61.52</u>	63.92	89.28	76.60
JSON	44.40	65.12	54.76	**64.88**	<u>89.84</u>	**77.36**
Code	50.16	71.20	60.68	<u>64.24</u>	**90.16**	<u>77.20</u>

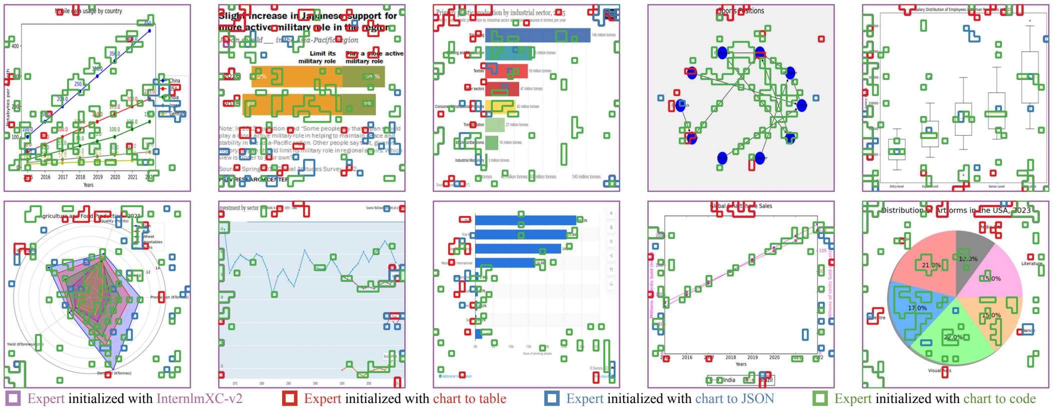


Figure 6: Visualizations of top-1 expert selection. Only the boundaries of the merged tokens are plotted.

(+1.52%↑). When combined with our proposed MoE connector, performance further increases to 78.76%, a total gain of +3.08%↑ in Acc.@0.05.

Effect of Supervise Fine-Tuning Strategy. As shown in rows 4-5 of Tab. 6, we divide the supervised fine-tuning stage into two phases. By incorporating high-quality knowledge learning using the MMC dataset, ChartMoE achieves 79.04% Acc.@0.05, reflecting a 3.36% improvement. In the chart-specific annealing tuning phase, we introduce ChartGemma data to enhance the model's reasoning and PoT capabilities, leading the model to peak performance (81.20%, +5.52%↑).

5.3 In-depth Analysis

Effect of the Each Expert. To explore the role of each expert in ChartMoE, we bypass the gating network and manually select the output of specific experts. As shown in Tab. 7, E0 performs the best (79.80%), which is consistent with the distribution in Fig. 5. However, this doesn't mean other experts lack relevance, which may offer crucial insights at key moments (Fig. 6).

Effect of Alignment Task. As shown in Tab. 8, we explore various alignment tasks based on the linear connector. After alignment, the performance on ChartQA declines compared to the baseline. However, the aligned model exhibits a substantial improvement after supervised fine-tuning on the ChartQA train split, which is consistent with previous observations Meng et al. (2024); Yan et al. (2024). Specifically, the JSON and code tasks exhibit remarkable improvement over the table.

Expert Distribution Visualization. As shown in Fig. 5& 6, we visualize the expert distribution in the MoE connector on the ChartBench test set. We designate the vanilla connector as E0, while E1-3 corresponds to connectors aligned with tables, JSON, and code. As depicted in Fig. 5, the trend is consistent across different chart types, with E0 and E3 being the most frequently selected

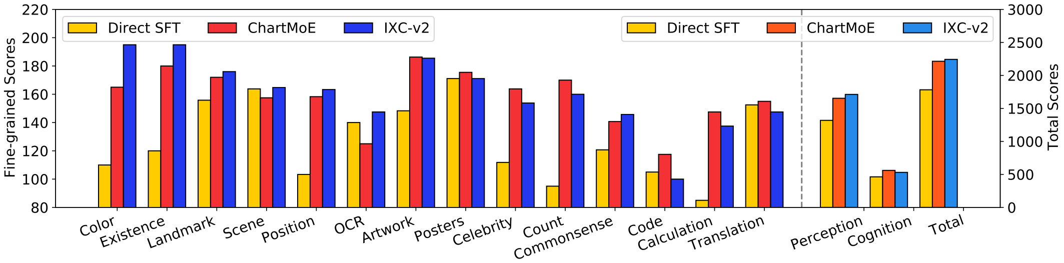


Figure 7: The performance on the general VQA tasks (MME Fu et al. (2023)). With supervised fine-tuning on extensive chart-structured data, the directly tuned IXC-v2 shows a significant performance drop, while ChartMoE maintains a satisfying performance by keeping the vanilla connector as the expert in MoE.

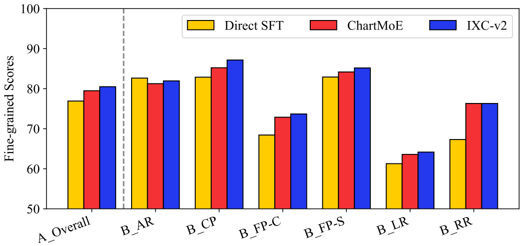


Figure 8: The performance on the general VQA tasks (MMBench Liu et al. (2023e)). Please refer to its paper for each task's details. The observations and conclusions are consistent with the MME benchmark.

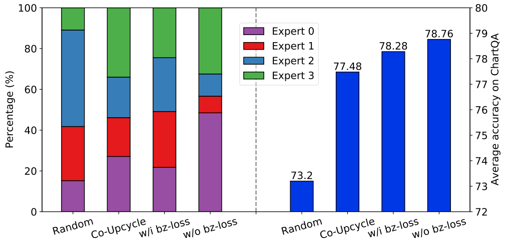


Figure 9: The performance with/without bz-loss on ChartQA. Left: The bz-loss leads to more even expert selections. Right: A more balanced distribution does not yield better performance.

connectors. The expert selection shows no extreme bias, as even the least chosen, E1, accounts for over 10%. We further visualize the expert selection for each image token, revealing the preferences of each expert. As shown in Fig. 6, E0 is the primary choice for background tokens, explaining its dominance in Fig. 5. E1 and E2 are more frequently chosen by tokens from titles, axis labels, or legends, as these elements are commonly found in tables and JSON files. ChartMoE tends to use E3 to focus on the data points and visual elements within the chart, e.g., data points on the line, digital text, and edges in a node chart. These components are essential for accurately re-drawing the charts.

Performance on General Tasks. While ChartMoE is designed to enhance chart understanding, it does not compromise other capabilities, e.g., instruction following and object recognition. In Fig. 7& 8, we show the comparisons of directly fine-tuned InternlmXC-v2 (short for Direct SFT) with data from Tab. 1 and the baseline (short for IXC-v2) on general benchmarks Fu et al. (2023); Liu et al. (2023e). The direct SFT model shows diminished general capabilities. In contrast, ChartMoE preserves it nearly intact by retaining the original connector as one of its experts.

Effect of Balance Loss in MoE. The standard MoE Zoph et al. (2022) employs balanced loss and router z-loss (short for bz-loss) to prevent certain experts from dominating the model training. In Fig. 9, we compare the effects of with and without bz-loss. While bz-loss promotes a more equitable selection of experts, it fails to enhance ChartMoE's performance further. As shown in Fig. 6, the expert initialization in ChartMoE results in each expert having its own preference for visual token selection (refer to Appendix B for detail). Consequently, the bz-loss might hinder the model's convergence to the optimal point because the distribution of visual tokens is inherently imbalanced.

6 Conclusion

We introduce ChartMoE, a multi-task aligned and instruction-tuned MLLM designed for complex chart understanding and reasoning. We replace the linear connector with the MoE architecture and initialize each expert with parameters derived from different alignment tasks. We further present the ChartMoE-Align dataset, a synthetic collection of nearly 1 million table-json-code-chart quadruples, to facilitate alignment training across different experts. This approach preserves the strengths of each alignment task, ensuring efficient training and superior model performance. ChartMoE outperforms the previous state-of-the-art on several benchmarks by a large margin and excels in real-world applications such as chart question answering, translation, and editing. Please refer to Appendix A.3 for the reproducibility statement.

7 ACKNOWLEDGMENTS

This work was supported by the National Key R&D Program of China (2022YFB4701400/4701402), SSTIC Grant(KJZD20230923115106012, KJZD20230923114916032, GJHZ2024021811360408), and Beijing Key Lab of Networked Multimedia.

REFERENCES

Mubashara Akhtar, Oana Cocarascu, and Elena Paslaru Bontas Simperl. Reading and reasoning over chart images for evidence-based automated fact-checking. *arXiv preprint:2301.11843*, 2023a.

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:2311.07453*, 2023b.

Jean-Baptiste Alayrac, Jeff Donahue, Pauline Luc, et al. Flamingo: a visual language model for few-shot learning. In *proceedings of NeurIPS*, volume 35, pp. 23716–23736, 2022.

Alibaba. Qwen-vl 2.5: A multimodal large language model. https://tongyi.aliyun.com/qianwen, 2024. Accessed: 2024-09-17.

Jinze Bai, Shuai Bai, Yunfei Chu, et al. Qwen technical report. *arXiv preprint:2309.16609*, 2023a.

Jinze Bai, Shuai Bai, Shusheng Yang, et al. Qwen-vl: A frontier large vision-language model with versatile abilities. *arXiv preprint:2308.12966*, 2023b.

Lucas Beyer, Andreas Steiner, André Susano Pinto, et al. Paligemma: A versatile 3b vlm for transfer. *arXiv preprint:2407.07726*, 2024.

Tom Brown, Benjamin Mann, Nick Ryder, et al. Language models are few-shot learners. In *proceedings of NeurIPS*, volume 33, pp. 1877–1901, 2020.

Victor Carbune, Hassan Mansoor, Fangyu Liu, et al. Chart-based reasoning: Transferring capabilities from llms to vlms. In *proceedings of NAACL*, 2024.

Jinyue Chen, Lingyu Kong, Haoran Wei, Chenglong Liu, Zheng Ge, Liang Zhao, Jianjian Sun, Chunrui Han, and Xiangyu Zhang. Onechart: Purify the chart structural extraction via one auxiliary token. *arXiv preprint:2404.09987*, 2024.

Jun Chen, Deyao Zhu, Xiaoqian Shen, et al. Minigpt-v2: large language model as a unified interface for vision-language multi-task learning. *arXiv preprint:2310.09478*, 2023.

Tri Dao. FlashAttention-2: Faster attention with better parallelism and work partitioning. In *International Conference on Learning Representations (ICLR)*, 2024.

Xiaoyi Dong, Pan Zhang, Yuhang Zang, et al. Internlm-xcomposer2: Mastering free-form text-image composition and comprehension in vision-language large model. *arXiv preprint:2401.16420*, 2024.

Chaoyou Fu, Peixian Chen, Yunhang Shen, et al. Mme: A comprehensive evaluation benchmark for multimodal large language models. *arXiv preprint:2306.13394*, 2023.

Yucheng Han, Chi Zhang, Xin Chen, et al. Chartllama: A multimodal llm for chart understanding and generation. *arXiv preprint:2311.16483*, 2023.

Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun. Deep residual learning for image recognition. In *proceedings of CVPR*, pp. 770–778, 2016.

Enamul Hoque, Vidya Setlur, Melanie Tory, and Isaac Dykeman. Applying pragmatics principles for interaction with visual analytics. *IEEE TVCG*, 24(1):309–318, 2017.

Ting-Yao Hsu, C Lee Giles, and Ting-Hao'Kenneth' Huang. Scicap: Generating captions for scientific figures. In *Findings of ACL*, 2021.

Anwen Hu, Haiyang Xu, Jiabo Ye, Ming Yan, Liang Zhang, Bo Zhang, Chen Li, Ji Zhang, Qin Jin, Fei Huang, et al. mplug-docowl 1.5: Unified structure learning for ocr-free document understanding. *arXiv preprint:2403.12895*, 2024.

Edward J Hu, Yelong Shen, Phillip Wallis, et al. LoRA: Low-rank adaptation of large language models. In *proceedings of ICLR*, 2022.

Kung-Hsiang Huang, Hou Pong Chan, Yi R. Fung, Haoyi Qiu, Mingyang Zhou, Shafiq Joty, Shih-Fu Chang, and Heng Ji. From pixels to insights: A survey on automatic chart understanding in the era of large foundation models, 2024.

Aran Komatsuzaki, Joan Puigcerver, James Lee-Thorp, et al. Sparse upcycling: Training mixture-of-experts from dense checkpoints. In *proceedings of ICLR*, 2023.

Kenton Lee, Mandar Joshi, Iulia Raluca Turc, et al. Pix2struct: Screenshot parsing as pretraining for visual language understanding. In *proceedings of ICML*, pp. 18893–18912, 2023.

Jiachen Li, Xinyao Wang, Sijie Zhu, Chia-Wen Kuo, Lu Xu, Fan Chen, Jitesh Jain, Humphrey Shi, and Longyin Wen. Cumo: Scaling multimodal llm with co-upcycled mixture-of-experts. *arXiv preprint:2405.05949*, 2024.

Junnan Li, Dongxu Li, Silvio Savarese, et al. BLIP-2: bootstrapping language-image pre-training with frozen image encoders and large language models. In *proceedings of ICML*, volume 202, pp. 19730–19742, 2023.

Bin Lin, Zhenyu Tang, Yang Ye, Jiaxi Cui, Bin Zhu, Peng Jin, Junwu Zhang, Munan Ning, and Li Yuan. Moe-llava: Mixture of experts for large vision-language models. *arXiv preprint arXiv:2401.15947*, 2024.

Ziyi Lin, Chris Liu, Renrui Zhang, et al. Sphinx: The joint mixing of weights, tasks, and visual embeddings for multi-modal large language models. *arXiv preprint:2311.07575*, 2023.

Fangyu Liu, Julian Martin Eisenschlos, Francesco Piccinno, Syrine Krichene, et al. Deplot: One-shot visual language reasoning by plot-to-table translation. In *Findings of ACL*, pp. 10381–10399, 2023a.

Fangyu Liu, Francesco Piccinno, Syrine Krichene, et al. Matcha: Enhancing visual language pretraining with math reasoning and chart derendering. In *proceedings of ACL*, pp. 12756–12770, 2023b.

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. In *proceedings of ACL*, 2023c.

Haotian Liu, Chunyuan Li, Qingyang Wu, and Yong Jae Lee. Visual instruction tuning. In *proceedings of NeurIPS*, 2023d.

Haotian Liu, Chunyuan Li, Yuheng Li, Bo Li, Yuanhan Zhang, Sheng Shen, and Yong Jae Lee. Llava-next: Improved reasoning, ocr, and world knowledge, January 2024a. URL https://llava-vl.github.io/blog/2024-01-30-llava-next/.

Haotian Liu, Chunyuan Li, Yuheng Li, et al. Improved baselines with visual instruction tuning. In *proceedings of CVPR*, 2024b.

Mengsha Liu, Daoyuan Chen, Yaliang Li, Guian Fang, and Ying Shen. Chartthinker: A contextual chain-of-thought approach to optimized chart summarization. *arXiv preprint:2403.11236*, 2024c.

Yuan Liu, Haodong Duan, Yuanhan Zhang, et al. Mmbench: Is your multi-modal model an all-around player? *arXiv preprint:2307.06281*, 2023e.

Haoyu Lu, Wen Liu, Bo Zhang, Bingxuan Wang, Kai Dong, Bo Liu, Jingxiang Sun, Tongzheng Ren, Zhuoshu Li, Hao Yang, et al. Deepseek-vl: towards real-world vision-language understanding. *arXiv preprint:2403.05525*, 2024.

Ahmed Masry, Do Xuan Long, Jia Qing Tan, et al. Chartqa: A benchmark for question answering about charts with visual and logical reasoning. In *proceedings of ACL*, 2022.

Ahmed Masry, Parsa Kavehzadeh, Xuan Long Do, Enamul Hoque, and Shafiq Joty. Unichart: A universal vision-language pretrained model for chart comprehension and reasoning. In *proceedings of EMNLP*, 2023.

Ahmed Masry, Mehrad Shahmohammadi, Md Rizwan Parvez, Enamul Hoque, and Shafiq Joty. Chartinstruct: Instruction tuning for chart comprehension and reasoning. *arXiv preprint:2403.09028*, 2024a.

Ahmed Masry, Megh Thakkar, Aayush Bajaj, Aaryaman Kartha, Enamul Hoque, and Shafiq Joty. Chartgemma: Visual instruction-tuning for chart reasoning in the wild. *arXiv preprint:2407.04172*, 2024b.

Fanqing Meng, Wenqi Shao, Quanfeng Lu, et al. Chartassisstant: A universal chart multimodal language model via chart-to-table pre-training and multitask instruction tuning. *arXiv preprint:2401.02384*, 2024.

Nitesh Methani, Pritha Ganguly, Mitesh M Khapra, and Pratyush Kumar. Plotqa: Reasoning over scientific plots. In *proceedings of CVPR*, pp. 1527–1536, 2020.

OpenAI. Gpt-4 technical report. *arXiv preprint:2303.08774*, 2023.

OpenAI. Gpt-4o: A multimodal large language model. https://openai.com, 2024. Accessed: 2024-09-17.

Maxime Oquab, Timothée Darcet, Théo Moutakanni, et al. Dinov2: Learning robust visual features without supervision. *TMLR*, 2023.

Alec Radford, Karthik Narasimhan, Tim Salimans, Ilya Sutskever, et al. Improving language understanding by generative pre-training. *OpenAI blog*, 2018.

Alec Radford, Jong Wook Kim, Chris Hallacy, et al. Learning transferable visual models from natural language supervision. In *proceedings of ICML*, pp. 8748–8763. PMLR, 2021.

Gemma Team, Thomas Mesnard, Cassidy Hardin, et al. Gemma: Open models based on gemini research and technology. *arXiv preprint:2403.08295*, 2024a.

Gemma Team, Thomas Mesnard, Cassidy Hardin, et al. Gemma: Open models based on gemini research and technology. *arXiv preprint:2407.21783*, 2024b.

Shengbang Tong, Ellis Brown, Penghao Wu, Sanghyun Woo, Manoj Middepogu, Sai Charitha Akula, Jihan Yang, Shusheng Yang, Adithya Iyer, Xichen Pan, et al. Cambrian-1: A fully open, vision-centric exploration of multimodal llms. *arXiv preprint arXiv:2406.16860*, 2024a.

Shengbang Tong, Zhuang Liu, Yuexiang Zhai, Yi Ma, Yann LeCun, and Saining Xie. Eyes wide shut? exploring the visual shortcomings of multimodal llms. In *Proceedings of CVPR*, pp. 9568–9578, 2024b.

Hugo Touvron, Thibaut Lavril, Gautier Izacard, et al. Llama: Open and efficient foundation language models. *arXiv preprint:2302.13971*, 2023.

Peifang Wang, Olga Golovneva, Armen Aghajanyan, et al. DOMINO: A dual-system for multi-step visual language reasoning. *arXiv preprint:2310.02804*, 2023.

Jason Wei, Xuezhi Wang, Dale Schuurmans, et al. Chain-of-thought prompting elicits reasoning in large language models. In *proceedings of NeurIPS*, volume 35, pp. 24824–24837, 2022.

Yifan Wu, Lutao Yan, Yuyu Luo, Yunhai Wang, and Nan Tang. Evaluating task-based effectiveness of mllms on charts. *arXiv preprint:2405.07001*, 2024.

Renqiu Xia, Bo Zhang, Hancheng Ye, Xiangchao Yan, et al. Chartx & chartvlm: A versatile benchmark and foundation model for complicated chart reasoning. *arXiv preprint:2402.12185*, 2024.

Zhengzhuo Xu, Sinan Du, Yiyan Qi, Chengjin Xu, Chun Yuan, and Jian Guo. Chartbench: A benchmark for complex visual reasoning in charts. *arXiv preprint:2312.15915*, 2023.

Le Xue, Manli Shu, Anas Awadalla, Jun Wang, An Yan, Senthil Purushwalkam, Honglu Zhou, Viraj Prabhu, Yutong Dai, Michael S Ryoo, et al. xgen-mm (blip-3): A family of open large multimodal models. *arXiv preprint:2408.08872*, 2024.

Pengyu Yan, Mahesh Bhosale, Jay Lal, Bikhyat Adhikari, and David S. Doermann. Chartreformer: Natural language-driven chart image editing. *arXiv preprint:2403.00209*, 2024.

Jiabo Ye, Anwen Hu, Haiyang Xu, et al. Ureader: Universal ocr-free visually-situated language understanding with multimodal large language model. In *Findings of ACL*, 2023a.

Qinghao Ye, Haiyang Xu, Guohai Xu, et al. mplug-owl: Modularization empowers large language models with multimodality. *arXiv preprint:2304.14178*, 2023b.

Qinghao Ye, Haiyang Xu, Jiabo Ye, et al. mplug-owl2: Revolutionizing multi-modal large language model with modality collaboration. *arXiv preprint:2311.04257*, 2023c.

Xiaohua Zhai, Basil Mustafa, Alexander Kolesnikov, and Lucas Beyer. Sigmoid loss for language image pre-training. In *proceedings of ICCV*, pp. 11975–11986, 2023.

Liang Zhang, Anwen Hu, Haiyang Xu, Ming Yan, Yichen Xu, Qin Jin, Ji Zhang, and Fei Huang. Tinychart: Efficient chart understanding with visual token merging and program-of-thoughts learning. *arXiv preprint:2404.16635*, 2024.

Pan Zhang, Xiaoyi Dong Bin Wang, Yuhang Cao, Chao Xu, et al. Internlm-xcomposer: A vision-language large model for advanced text-image comprehension and composition. *arXiv preprint:2309.15112*, 2023.

Susan Zhang, Stephen Roller, Naman Goyal, et al. Opt: Open pre-trained transformer language models. *arXiv preprint:2205.01068*, 2022.

Lianmin Zheng, Wei-Lin Chiang, Ying Sheng, et al. Judging llm-as-a-judge with mt-bench and chatbot arena. In *proceedings of NeurIPS*, 2023.

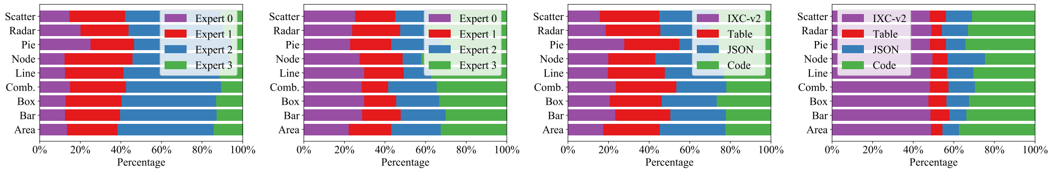
Li Zhuowan, Jasani Bhavan, Tang Peng, and Ghadar Shabnam. Synthesize step-by-step: Tools, templates and llms as data generators for reasoning-based chart vqa. In *proceedings of CVPR*, 2024.

Barret Zoph, Irwan Bello, Sameer Kumar, Nan Du, Yanping Huang, Jeff Dean, Noam M. Shazeer, and William Fedus. St-moe: Designing stable and transferable sparse expert models. *arXiv preprint:2202.08906*, 2022.

A Additional Experimental Settings and Results

A.1 Top-2 Experts Distribution

Our ChartMoE employs MoE connector expert parameters initialized with various alignment tasks. To investigate the impact of these initialization methods on model performance, we present the comparisons in Tab. 6& 7& 8 and Fig. 4&5. For a deeper analysis, we explore how different initialization methods affect expert selection. As shown in Fig. 10, both random initialization and co-upcycle result in a more uniform distribution of experts. However, this uniformity does not inherently lead to improved performance or interpretability, possibly due to insufficient differentiation among the experts. In contrast, our ChartMoE clearly prefers specialized roles, as illustrated in Fig. 6& 11& 12.



(a) Random (b) Co-Upcycle (c) ChartMoE with bz-loss (d) ChartMoE

Figure 10: The distribution of Top-2 experts after supervised fine-tuning with three expert initialization methods. We calculate the proportion of the top 2 experts selected by the router on the ChartBench.

A.2 Summary of Hyperparameter Settings

The training process of our ChartMoE is structured into three distinct phases: Alignment Pre-training, High-Quality Knowledge Learning, and Chart-Specific Annealing Tuning. Table 9 provides a comprehensive overview of the hyperparameter configurations employed during each training stage. It should be noted that using flash-attention Dao (2024) can effectively reduce GPU hours.

Table 9: Training hyperparameters of ChartMoE for all stages.

Configuration	**Alignment Pre-training**	**High-Quality Knowledge Learning**	**Chart Specific Annealing Tuning**
Connector Initialization	InternlmXC-v2	Table&JSON&Code Experts + InternlmXC-v2	ChartMoE 2nd-stage
LLM Training	Freeze	LoRA	LoRA
Image Resolution	490	490	490
ViT Sequence Length	1225	1225	1225
Optimizer	AdamW	AdamW	AdamW
Optimizer Hyperparameter	$\beta_1 = 0.9, \beta_2 = 0.95, \epsilon = 1e^{-8}$	$\beta_1 = 0.9, \beta_2 = 0.95, \epsilon = 1e^{-8}$	$\beta_1 = 0.9, \beta_2 = 0.95, \epsilon = 1e^{-8}$
Peak Learning Rate	$5e^{-5}$	$5e^{-5}$	$1e^{-5}$
Learning Rate Schedule	cosine decay	cosine decay	cosine decay
Weight Decay	0.1	0.1	0.1
Gradient Clip	1.0	1.0	1.0
Warm-up Ratio	0.01	0.01	0.01
Global Batch Size	256	64	64
Gradient Acc.	16	8	8
Numerical Precision	bfloat16	bfloat16	bfloat16
Optimizer Sharding	✓	✓	✓
Gradient Sharding	✓	✓	✓
Parameter Sharding	×	×	×
Activation Checkpointing	✓	✓	✓
GPU Hours (A100-40G)	210	100	56

A.3 Reproducibility Statement

We have included the architecture of ChartMoE in Section 3.1 and the complete training procedure in Section 3.2 and Section 3.3. The training data recipe is listed in Tab. 1 in detail. Hyper-parameter settings are shown in Appendix A.2. We also introduce the generation pipeline for ChartMoE-Align in Section 3.2, and some detailed examples in Appendix C. Furthermore, our ChartMoE-Align dataset and checkpoints of ChartMoE will be released soon on GitHub and Huggingface.

B Additional Vsualizations of Top-1 Expert Selection

In this section, we randomly sampled images from natural image datasets (LLaVA-CC3M Liu et al. (2023d)) and chart datasets (ChartQA Masry et al. (2022), ChartBench Xu et al. (2023)) to illustrate ChartMoE's token selection preferences. As shown in Fig. 11, the vanilla expert focuses more on the background, the table expert concentrates on details such as the boundary between the background and the subject, the JSON expert focuses on textures (e.g., maps and objects), and the code expert specializes in curves and trends (e.g., logos and text). Fig. 12 further demonstrates that while the vanilla expert continues to attend to background tokens, critical visual elements are handled by the aligned experts, with the code expert being notably more prominent.

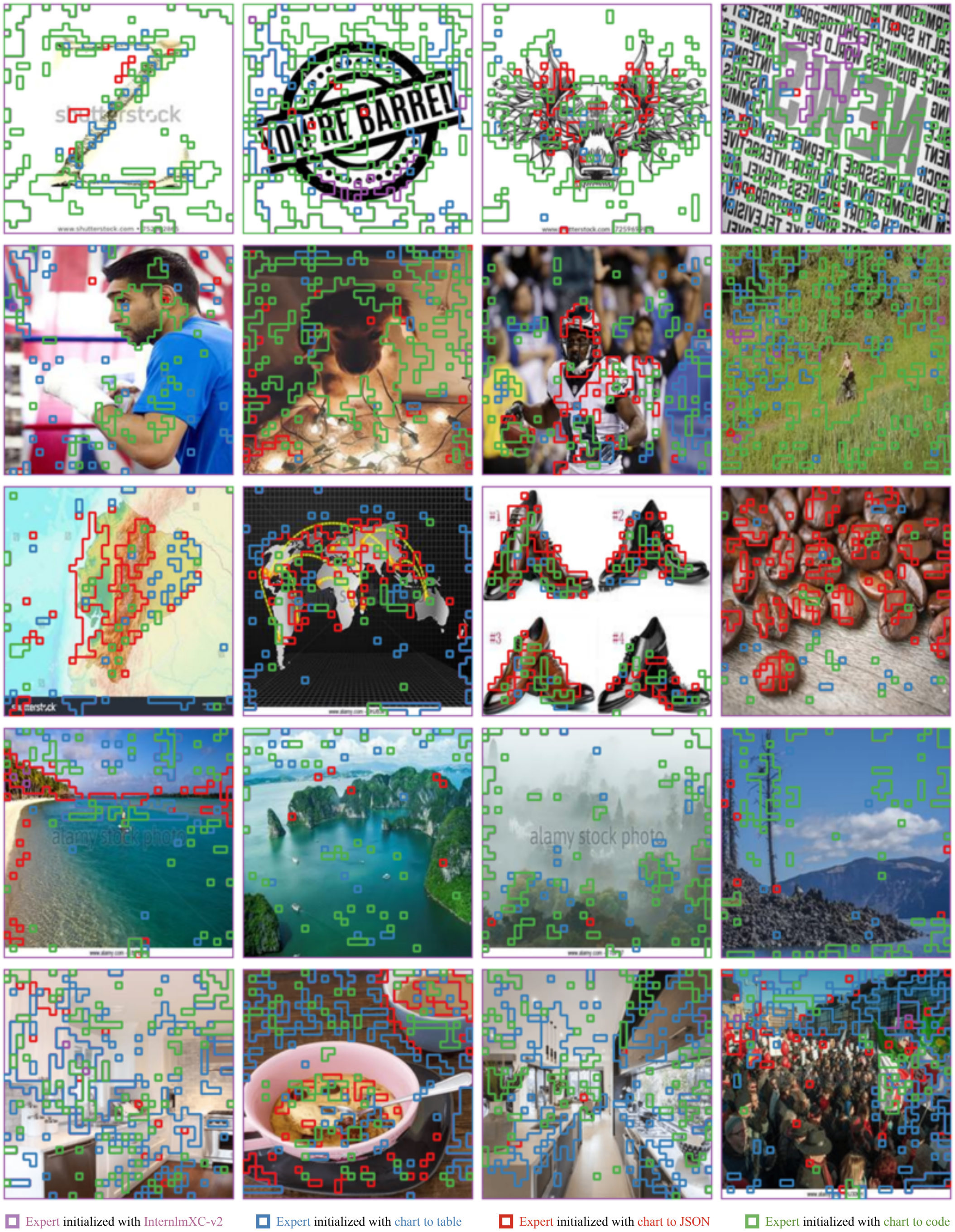

shutterstock
YOU'RE BARRED
NEWS
alamy stock photo
alamy stock photo
□ Expert initialized with InternlmXC-v2
□ Expert initialized with chart to table
□ Expert initialized with chart to JSON
□ Expert initialized with chart to code

Figure 11: More visualizations of top-1 expert selection on ***general images*** randomly sampled from LLaVA-CC3M. These examples show the selection preferences of different experts in ChartMoE.

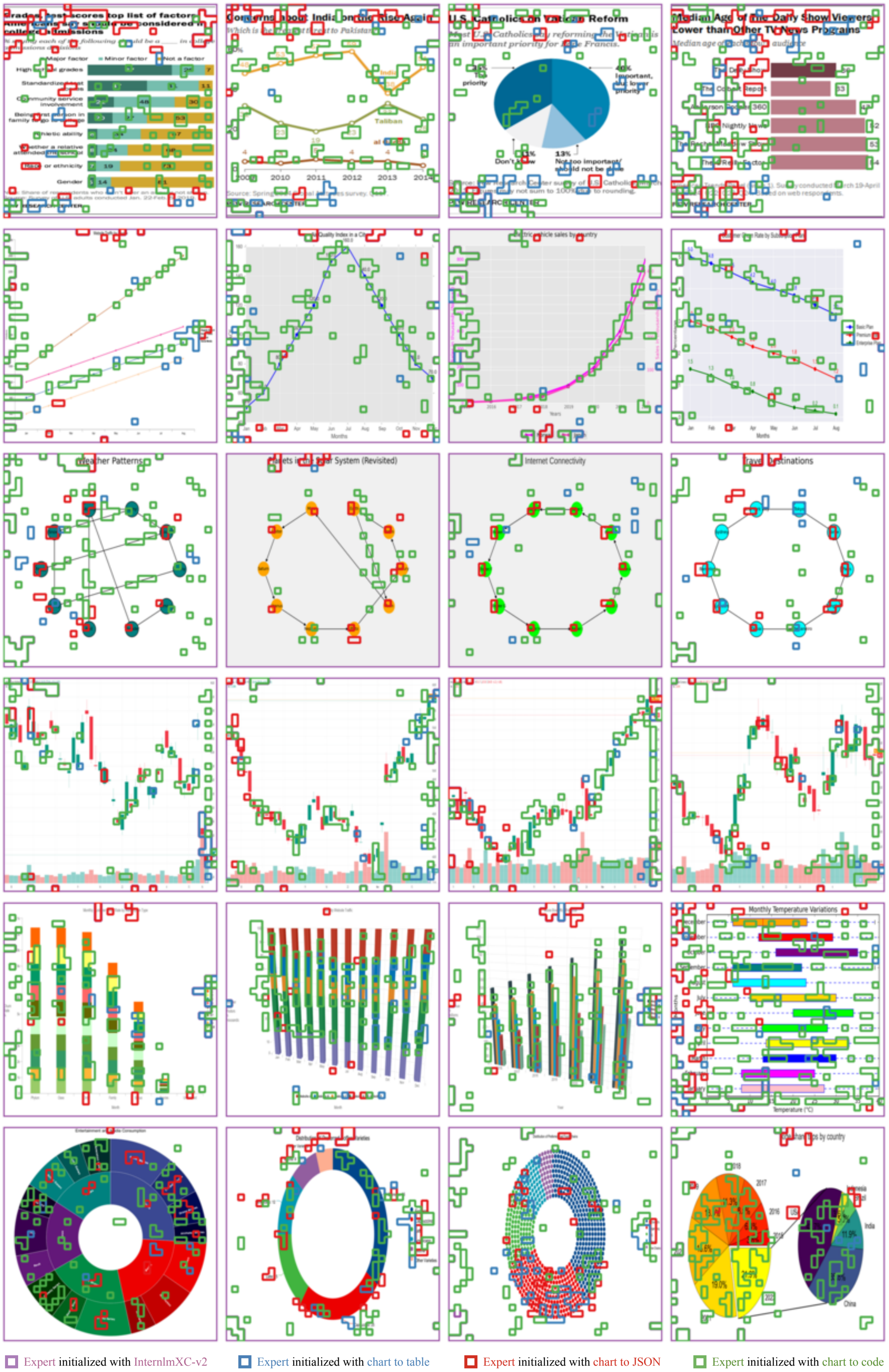


Figure 12: More visualizations of top-1 expert selection on ***chart images***. The vanilla expert primarily handles background tokens, and the chart visual markers are handled by other experts.

C Details of ChartMoE-Align

C.1 Overview

ChartMoE-Align is a dataset we introduced for different experts aligning pretraining. It consists of nearly 1 million Chart Table JSON Code quadruples and supports three alignment tasks: Chart to Table, Chart to JSON, and Chart to Code. Unlike other chart datasets, ChartMoE-Align focuses solely on these three fundamental alignment tasks without considering the diversity of instruction tasks.

C.2 Table Data Collection

We primarily collect table data from three sources: the ChartQA training set Masry et al. (2022), the PlotQA training set Methani et al. (2020), and ChartY provided by OneChart Chen et al. (2024).

ChartQA includes 18.3K real-world charts and provides accompanying meta tables. While the charts are of high quality and manually curated, they lack fine-grained attribute annotations and executable plotting code. As a result, we only retained the tables from ChartQA in CSV format.

PlotQA comprises 157K charts, primarily focusing on three common types: line, bar, and pie charts. These charts are generated using Python code with limited formatting and style diversity. Consequently, we did not utilize the charts from PlotQA but retained its 157K tables. These tables originate from sources like World Bank Open Data, Open Government Data, and the Global Terrorism Database, covering statistics on various indicators such as fertility rates, rainfall, coal production, and more across years, countries, and districts.

ChartY is a chart dataset containing 2.7M charts in both Chinese and English proposed by OneChart. Notably, ChartY also includes charts from ChartQA and PlotQA, which we filtered out in ChartMoE-Align. Additionally, ChartY primarily consists of common chart types such as line, bar, and pie charts (or their combinations) and suffers from significant data imbalance. To address this, we sampled a subset to ensure a roughly equal number of charts for each type. As the tables in ChartY are mainly generated by GPT-3.5 based on templates, we ultimately retained 763K samples from this source.

C.3 Pair Data Construction

JSON provides a structured format distinct from CSV, designed to retain chart attributes beyond numerical data, such as title position, font size, element colors, legend styles, and more. We adopt the template provided by ChartReformer Yan et al. (2024) and further enhance it. We add chart type-agnostic attributes like title position and gridlines. For chart type-specific attributes, we aim to remain consistent with ChartReformer's definitions while accommodating all chart types present in ChartMoE-Align. With this framework, we generate corresponding JSON files for all tables. To extract chart type-specific attributes, we fine-tune a Deplot Liu et al. (2023a) model, leveraging the original chart to extract their properties. Missing attributes are filled in using random sampling to ensure completeness.

Code refers to Python scripts based on *matplotlib* for rendering the charts. Leveraging the rich attributes defined in the JSON, the code is designed to faithfully represent every attribute to ensure diversity in the resulting charts. During generation, we explicitly specify all default parameters, such as the hexadecimal color codes for each line/bar, default font sizes, text positions, etc. We provide basic code templates for type-agnostic attributes. For type-specific attributes, rules are used to automatically generate the corresponding code.

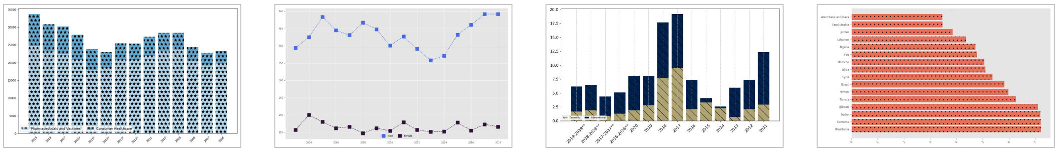
Chart is produced by executing the generated code. Given the number of table, JSON, and code pairs, we filter out any quadruples with execution errors or warnings during the chart generation process, retaining only valid and error-free samples.

Instruction. Considering the alignment task, we directly employ several templated questions to define the Chart-to-X tasks (X is the ground truth). Ultimately, each quadruple corresponds to three QA pairs. Note that ChartMoE-Align only serves for alignment training to initialize different expert projectors, thus emphasizing the diversity of charts and aligned modalities. To improve model performance and instruction-following, we still require more diverse instructions for supervised fine-tuning to update the MoE connector and LLM.

C.4 Quality Control

We first remove all duplicate entries from the meta table and then eliminate quadruples that cause errors or warnings during rendering. To further assess the quality of ChartMoE-Align, we randomly sample 200 quadruples and ask GPT-4o and annotation experts (with at least three experts reviewing each quadruple) to evaluate the clarity and readability of the charts, as well as the alignment between the charts and table/JSON/code, scoring them as 0 or 1. The results show that nearly all charts are clear, unambiguous, and free from obstructions (GPT-4o: 96.5%, Experts: 99%). Over 90% of the pairs are matching and suitable for instruction tuning (GPT-4o: 91%, Experts: 94.5%).

C.5 Example Visualization



(a) Charts in ChartMoE-Align.

```
Characteristic,Pharmaceuticals
and Vaccines,Consumer Healthcare
2020,24038,10033
2019,24711,8995
2018,23163,7658
2017,22436,7750
2016*,20696,7193
2015*,17813,6038
2014*,18597,4322
2013*,20743,4713
2012*,20645,4731
2011,21894,5403
2010,23284,5108
2009,23653,4715
2008,20381,3971
2007,19163,3553
2006,20013,3212
```

```
Characteristic,Male,Female
2019,486,144
2018,492,166
2017,492,173
2016,461,155
2015,432,178
2014,371,152
2013,358,151
2012,391,157
2011,427,179
2010,401,154
2009,448,162
2008,467,147
2007,431,166
2006,445,162
2005,484,180
2004,425,200
2003,394,157
2002,375,207
2001,391,162
2000,397,149
```

```
Characteristic,"Deaths per 1,000
inhabitants"
Somalia,10.86
Mauritania,7.22
Comoros,7.21
Sudan,7.19
Djibouti,7.1
Tunisia,6.26
Yemen,5.98
Egypt,5.82
Syria,5.37
Libya,5.1
Morocco,5.06
Iraq,4.78
Algeria,4.72
Lebanon,4.36
Jordan,3.86
Saudi Arabia,3.47
West Bank and Gaza,3.46
Kuwait,2.7
Oman,2.44
Bahrain,2.39
United Arab Emirates,1.47
Qatar,1.2
```

```
Characteristic,Domestic,Internat
ional
2020-2040**,1.9%,4.2%
2019-2039**,1.7%,4.5%
2018-2038**,1.9%,4.6%
2017-2037**,0.9%,3.5%
2016-2036**,1.3%,3.8%
2020,1.9%,6.2%
2019,2.8%,-1.3%
2018,7.7%,10%
2017,9.5%,9.7%
2016,2.1%,-1.3%
2015,3.3%,0.8%
2014,2.3%,0.3%
2013,0.7%,-7.5%
2012,2.1%,-3.8%
2011,-6.1%,9.4%
```

(b) Tables in ChartMoE-Align.

```
{
  "type_agnostic": {
    "x_font_name": "sans-serif",
    "x_font_size": "x-large",
    "y_font_name": "monospace",
    "y_font_size": "x-large",
    "x_tick_size": "small",
    "x_tick_rotation": 45,
    "y_tick_size": "small",
    "legend_loc": "lower left",
    "legend_ncols": 3,
    "legend_font_size": "medium",
    "title_font_name": "monospace",
    "title_font_size": "medium",
    "grid_vis": false,
    "grid_axi": "x",
    "grid_which": "minor",
    "grid_line_style": "solid",
    "vis_tool": "default"
  },
  "type_specific": {
    "colormap": "Blues",
    "hatch": "*",
    "align": "center"
  },
  "layout": {
    "title": "",
    "plot_labels": [
    "Pharmaceuticals and Vaccines",
    "Consumer Healthcare"
    ]
  }
}
```

```
{
  "type_agnostic": {
    "x_font_name": "Serif",
    "x_font_size": "large",
    "y_font_name": "sans-serif",
    "y_font_size": "medium",
    "x_tick_size": "x-small",
    "x_tick_rotation": 0,
    "y_tick_size": "large",
    "legend_loc": "lower center",
    "legend_ncols": 2,
    "legend_font_size": "x-small",
    "title_font_name": "monospace",
    "title_font_size": "medium",
    "grid_vis": true,
    "grid_axi": "y",
    "grid_which": "minor",
    "grid_line_style": "solid",
    "vis_tool": "ggplot"
  },
  "type_specific": {
    "colormap": "turbo",
    "marker": "s",
    "style": "--",
    "linewidth": 1.0,
    "markersize": 10
  },
  "layout": {
    "title": "",
    "plot_labels": [
    "Male",
    "Female"
    ]
  }
}
```

```
{
  "type_agnostic": {
    "x_font_name": "sans-serif",
    "x_font_size": "large",
    "y_font_name": "Serif",
    "y_font_size": "x-large",
    "x_tick_size": "small",
    "x_tick_rotation": 45,
    "y_tick_size": "small",
    "legend_loc": "upper center",
    "legend_ncols": 3,
    "legend_font_size": "x-small",
    "title_font_name": "Serif",
    "title_font_size": "medium",
    "grid_vis": false,
    "grid_axi": "both",
    "grid_which": "major",
    "grid_line_style": "dashed",
    "vis_tool": "ggplot"
  },
  "type_specific": {
    "colormap": "plasma",
    "hatch": ".",
    "align": "center"
  },
  "layout": {
    "title": "",
    "plot_labels": []
  }
}
```

```
{
  "type_agnostic": {
    "x_font_name": "sans-serif",
    "x_font_size": "large",
    "y_font_name": "monospace",
    "y_font_size": "medium",
    "x_tick_size": "large",
    "x_tick_rotation": 45,
    "y_tick_size": "medium",
    "legend_loc": "lower left",
    "legend_ncols": 3,
    "legend_font_size": "x-small",
    "title_font_name": "Serif",
    "title_font_size": "x-large",
    "grid_vis": true,
    "grid_axi": "x",
    "grid_which": "major",
    "grid_line_style": "dashed",
    "vis_tool": "default"
  },
  "type_specific": {
    "colormap": "cividis",
    "hatch": "\\",
    "align": "center"
  },
  "layout": {
    "title": "",
    "plot_labels": [
    "Domestic",
    "International"
    ]
  }
}
```

(c) JSONs in ChartMoE-Align. JSON is combined with the table during alignment pre-training.

```
import matplotlib.pyplot as plt
import numpy as np

# vis tool
plt.style.use('default')

# data
x = ['2019', '2018', '2017', '2016*', '2015*', '2014*', '2013*', '2012*', '2011',
'2010', '2009', '2008', '2007', '2006']
y = [[24711, 23163, 22436, 20696, 17813, 18597, 20743, 20645, 21894, 23284, 23653,
20381, 19163, 20013], [8995, 7658, 7750, 7193, 6038, 4322, 4713, 4731, 5403, 5108,
4715, 3971, 3553, 3212]]

plt.figure(figsize=(10, 6))

# a vertical bar chart
plt.bar(x, y[0], label="Pharmaceuticals and Vaccines", color='#b0d2e7', hatch='*',
align='center')
plt.bar(x, y[1], bottom=np.sum(y[:1], axis=0), label="Consumer Healthcare",
color='#66abd4', hatch='*', align='center')

# set the tick of x/y
plt.xticks(fontsize='small', rotation=45)
plt.yticks(fontsize='small')

# set the global legend
plt.legend(loc='lower left', ncol=3, fontsize='medium')

# set the grid
plt.grid(visible=False)

# Automatically resize the image by tight_layout()
plt.tight_layout()
# save the chart
plt.savefig('output.png')
# Clear the current image state
plt.clf()
```

```
import matplotlib.pyplot as plt
import numpy as np

# vis tool
plt.style.use('ggplot')

# data
x = [2003, 2004, 2005, 2006, 2007, 2008, 2009, 2010, 2011, 2012, 2013, 2014, 2015,
2016, 2017, 2018]
y = [[394, 425, 484, 445, 431, 467, 448, 401, 427, 391, 358, 371, 432, 461, 492,
492], [157, 200, 180, 162, 166, 147, 162, 154, 179, 157, 151, 152, 178, 155, 173,
166]]

plt.figure(figsize=(10, 6))

# a line chart
plt.plot(x,y[0], label="Male", color='#466be3', marker='s', markersize=10,
linestyle='--', linewidth=1.0)
plt.plot(x,y[1], label="Female", color='#30123b', marker='s', markersize=10,
linestyle='--', linewidth=1.0)

# set the tick of x/y
plt.xticks(fontsize='x-small', rotation=0)
plt.yticks(fontsize='x-small')

# set the global legend
plt.legend(loc='lower center', ncol=2, fontsize='x-small')

# set the grid
plt.grid(visible=True, which='minor', linestyle='solid', axis='y')

# Automatically resize the image by tight_layout()
plt.tight_layout()
# save the chart
plt.savefig('output.png')
# Clear the current image state
plt.clf()
```

(d) Codes in ChartMoE-Align. All values and attributes are expressed explicitly.

Figure 13: Detailed Examples in ChartMoE-Align. Each quadruple contains the chart, table, JSON and code.

D Further Discussion

D.1 Contribution of ChartMoE

Some prior work, such as MoE-LLaVA Lin et al. (2024), DeepSeek-VL Lu et al. (2024), and CuMo Li et al. (2024), has employed MoE architectures in MLLMs. However, these approaches all apply MoE to LLMs or ViTs to increase model capacity, introducing a large number of learnable parameters to boost performance. In contrast, our ChartMoE introduces several distinctive innovations:

1) Motivation: Our goal is not to expand model capacity but to enhance the model's chart comprehension through alignment tasks while preserving performance on other general tasks. Hence, we retain the original connector parameters as one expert initialization manner.

2) Initialization: Unlike previous methods that rely on random or co-upcycle initialization, we leverage multiple alignment tasks for expert (connector) initialization. This approach enables ChartMoE to exhibit remarkable interpretability (Fig. 6& 11& 12).

3) Complexity: We are the first to apply MoE exclusively to the MLP connector (projector) in LLaVA-like MLLMs. In ChartMoE (based on InternlmXC-v2), the MoE architecture introduces minimal additional parameters (model size 8.364B → 8.427B, + 63M↑ only) and training complexity (Fig. 4). It also shows negligible impact on inference speed (0.945 → 0.952 seconds per QA on ChartQA test set) and peak memory usage (23.72 GB → 23.86 GB, *fp16* on A100-40G GPU).

D.2 ChartMoE based on Other MLLMs

Our ChartMoE is based on InterlmXC-v2, but our proposals (MoE connector, diverse alignment, etc.) are general approaches. Therefore, we use 10% of the alignment data (Tab. 1) and the ChartQA training data to train our proposals based on LLaVA-v1.5-7B to further demonstrate their effectiveness. As shown in Tab. 10, our proposals significantly improve the base model. This is partly because LLaVA is trained with fewer chart data, leading to a lower baseline, and also indicates that the additional alignment data greatly enhances chart understanding.

Table 10: Performance comparison on ChartQA with LLaVA-v1.5-7B as base MLLM.

Models	Relax Acc @0.05			Relax Acc @0.10			Relax Acc @0.20		
	Human	Aug	Avg	Human	Aug	Avg	Human	Aug	Avg
LLaVA-v1.5-7B	7.60	7.36	7.48	7.92	8.08	8.00	9.04	9.52	9.28
LLaVA-v1.5-7B + ChartQA	6.08	23.04	14.56	8.24	32.96	20.60	10.32	42.16	26.24
LLaVA-v1.5-7B + ChartMoE	18.13	32.11	25.12	20.20	42.32	31.36	24.24	52.12	38.18

D.3 Performance on ChartQA

In Tab. 2, our ChartMoE significantly outperforms SOTA. However, some models perform better than ours on the *Augment* part of the ChartQA test set. Given that the *Augment* part of ChartQA is considerably easier than the *Human* part, we conduct a more detailed analysis. We analyze the performance of various models on numeric (*Human*: 43%, *Augment*: 39%) and non-numeric (*Human*: 57%, *Augment*: 61%) questions. As shown in Tab. 11, ChartMoE excels in all subcategories except for non-numeric questions in the *Augment* part. We find that ChartMoE's errors primarily occur in string-matching tasks. For instance, a prediction of *It is between 2003 and 2005* is marked incorrect if the ground truth is *(2003, 2005)*. High accuracy in this category may indicate overfitting instead.

Table 11: Fine-grained performance comparison on ChartQA with error margin 5%.

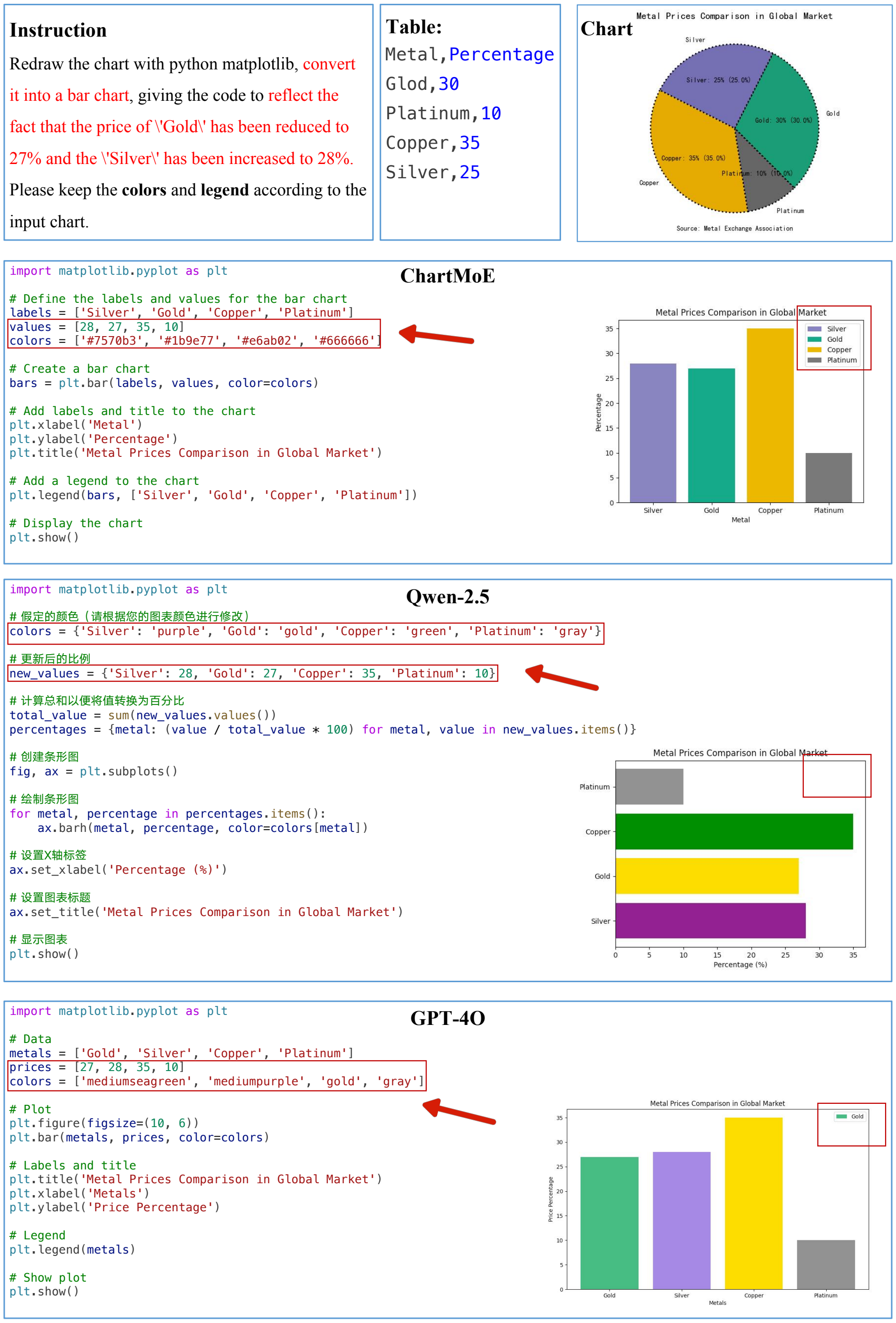
Method	Human			Augment			Acc
	Numeric	Non-Numeric	Avg	Numeric	Non-Numeric	Avg	
TinyChart	58.52%	58.03%	58.24%	92.43%	**96.25%**	94.32%	76.28%
ChartAst	67.04%	65.35%	66.08%	93.20%	**93.07%**	93.12%	79.00%
ChartMoE (Ours)	73.89%	75.49%	74.80%	93.20%	**90.98%**	91.84%	84.64%

D.4 Limitations

ChartMoE has two limitations: 1) Dependency on alignment tasks. ChartMoE requires chart-Table/JSON/Code alignment tasks for initialization. Non-chart multimodal tasks need new alignment designs to initialize MoE experts. 2) Limited flexibility. Modifying the projector into a multi-expert architecture makes ChartMoE non-plug-and-play like LoRA. We are required to retrain the router network when new experts are coming.

E Capability Comparisons on Chart Editing and Highlighting

ChartMoE, leveraging carefully designed alignment training, excels in accurately extracting chart values and attributes, facilitating precise image reconstruction, chart element editing, and highlighting. In this section, we provide a visual comparison with the SOTA MLLMs, Qwen-2.5 Alibaba (2024), and GPT-4O OpenAI (2024). While all three models perform the required instructions effectively, ChartMoE demonstrates superior accuracy in value and attribute extraction.



Instruction

Redraw the chart with python matplotlib, convert it into a bar chart, giving the code to reflect the fact that the price of \'Gold\' has been reduced to 27% and the \'Silver\' has been increased to 28%. Please keep the **colors** and **legend** according to the input chart.

Table:

Metal,Percentage
Glod,30
Platinum,10
Copper,35
Silver,25

Chart

ChartMoE

```
import matplotlib.pyplot as plt

# Define the labels and values for the bar chart
labels = ['Silver', 'Gold', 'Copper', 'Platinum']
values = [28, 27, 35, 10]
colors = ['#7570b3', '#1b9e77', '#e6ab02', '#666666']

# Create a bar chart
bars = plt.bar(labels, values, color=colors)

# Add labels and title to the chart
plt.xlabel('Metal')
plt.ylabel('Percentage')
plt.title('Metal Prices Comparison in Global Market')

# Add a legend to the chart
plt.legend(bars, ['Silver', 'Gold', 'Copper', 'Platinum'])

# Display the chart
plt.show()
```

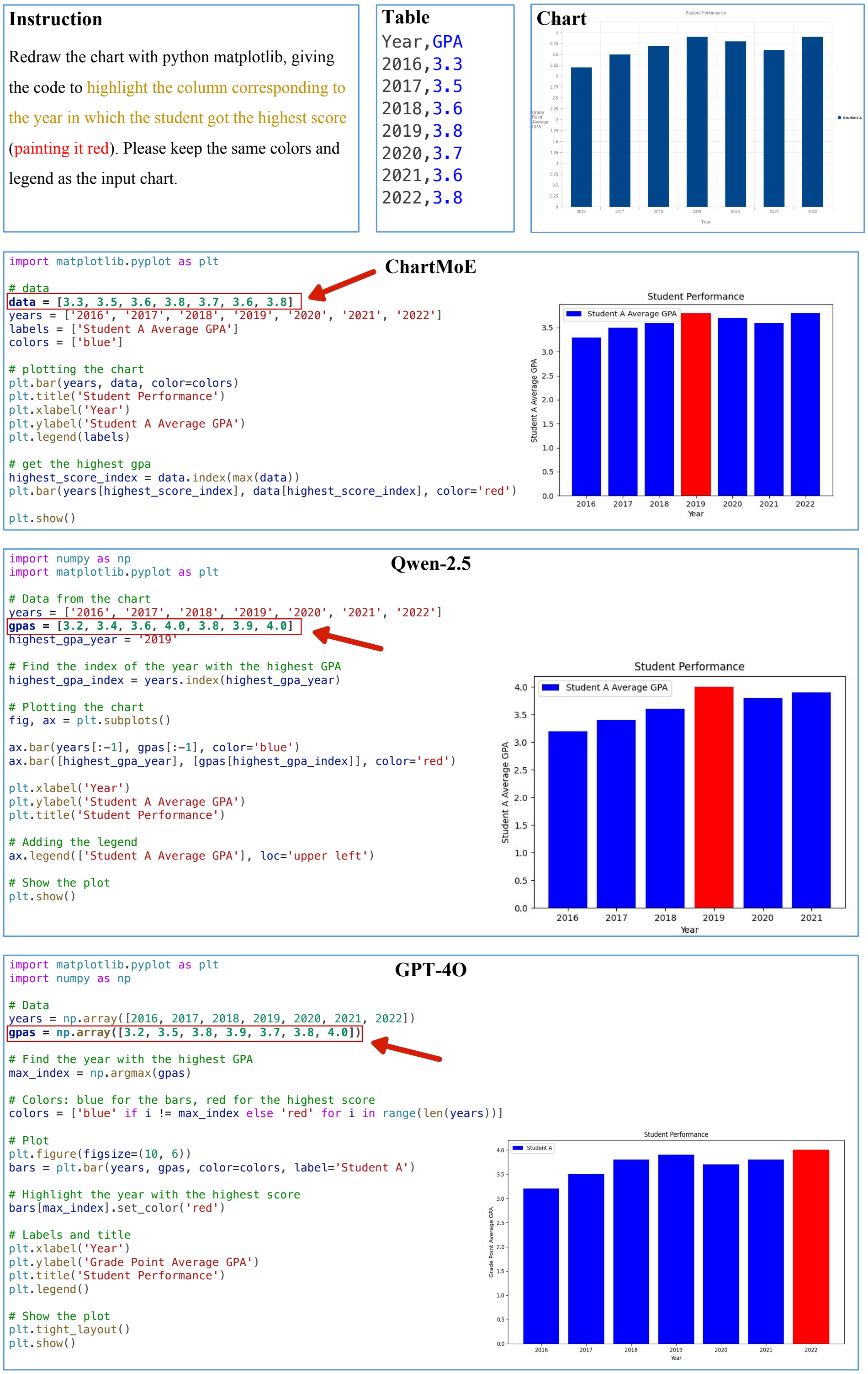
Qwen-2.5

```
import matplotlib.pyplot as plt

# 假定的颜色（请根据您的图表颜色进行修改）
colors = {'Silver': 'purple', 'Gold': 'gold', 'Copper': 'green', 'Platinum': 'gray'}

# 更新后的比例
new_values = {'Silver': 28, 'Gold': 27, 'Copper': 35, 'Platinum': 10}

# 计算总和以便将值转换为百分比
total_value = sum(new_values.values())
percentages = {metal: (value / total_value * 100) for metal, value in new_values.items()}

# 创建条形图
fig, ax = plt.subplots()

# 绘制条形图
for metal, percentage in percentages.items():
    ax.barh(metal, percentage, color=colors[metal])

# 设置X轴标签
ax.set_xlabel('Percentage (%)')

# 设置图表标题
ax.set_title('Metal Prices Comparison in Global Market')

# 显示图表
plt.show()
```

GPT-4O

```
import matplotlib.pyplot as plt

# Data
metals = ['Gold', 'Silver', 'Copper', 'Platinum']
prices = [27, 28, 35, 10]
colors = ['mediumseagreen', 'mediumpurple', 'gold', 'gray']

# Plot
plt.figure(figsize=(10, 6))
plt.bar(metals, prices, color=colors)

# Labels and title
plt.title('Metal Prices Comparison in Global Market')
plt.xlabel('Metals')
plt.ylabel('Price Percentage')

# Legend
plt.legend(metals)

# Show plot
plt.show()
```

Figure 14: Chat demo involves ***modifying chart types and values***. All models successfully convert the chart type, but only ChartMoE handles the legend correctly. No model makes errors in this task due to the simplicity of the values and the presence of data point labels.



Instruction

Redraw the chart with python matplotlib, giving the code to highlight the column corresponding to the year in which the student got the highest score (painting it red). Please keep the same colors and legend as the input chart.

Table

```
Year,GPA
2016,3.3
2017,3.5
2018,3.6
2019,3.8
2020,3.7
2021,3.6
2022,3.8
```

Chart

ChartMoE

```
import matplotlib.pyplot as plt

# data
data = [3.3, 3.5, 3.6, 3.8, 3.7, 3.6, 3.8]
years = ['2016', '2017', '2018', '2019', '2020', '2021', '2022']
labels = ['Student A Average GPA']
colors = ['blue']

# plotting the chart
plt.bar(years, data, color=colors)
plt.title('Student Performance')
plt.xlabel('Year')
plt.ylabel('Student A Average GPA')
plt.legend(labels)

# get the highest gpa
highest_score_index = data.index(max(data))
plt.bar(years[highest_score_index], data[highest_score_index], color='red')

plt.show()
```

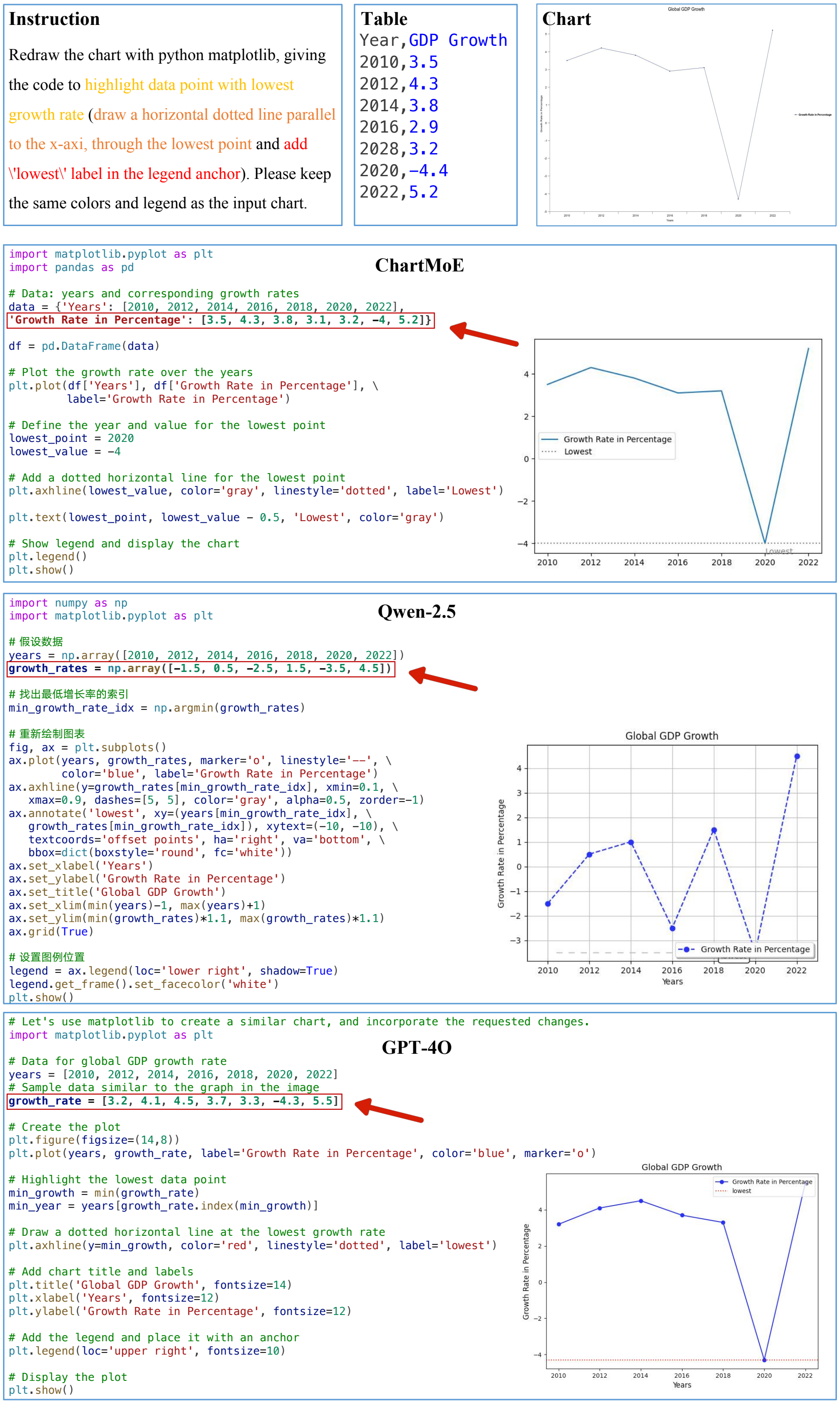
Qwen-2.5

```
import numpy as np
import matplotlib.pyplot as plt

# Data from the chart
years = ['2016', '2017', '2018', '2019', '2020', '2021', '2022']
gpas = [3.2, 3.4, 3.6, 4.0, 3.8, 3.9, 4.0]
highest_gpa_year = '2019'

# Find the index of the year with the highest GPA
highest_gpa_index = years.index(highest_gpa_year)

# Plotting the chart
fig, ax = plt.subplots()

ax.bar(years[:-1], gpas[:-1], color='blue')
ax.bar([highest_gpa_year], [gpas[highest_gpa_index]], color='red')

plt.xlabel('Year')
plt.ylabel('Student A Average GPA')
plt.title('Student Performance')

# Adding the legend
ax.legend(['Student A Average GPA'], loc='upper left')

# Show the plot
plt.show()
```

GPT-4O

```
import matplotlib.pyplot as plt
import numpy as np

# Data
years = np.array([2016, 2017, 2018, 2019, 2020, 2021, 2022])
gpas = np.array([3.2, 3.5, 3.8, 3.9, 3.7, 3.8, 4.0])

# Find the year with the highest GPA
max_index = np.argmax(gpas)

# Colors: blue for the bars, red for the highest score
colors = ['blue' if i != max_index else 'red' for i in range(len(years))]

# Plot
plt.figure(figsize=(10, 6))
bars = plt.bar(years, gpas, color=colors, label='Student A')

# Highlight the year with the highest score
bars[max_index].set_color('red')

# Labels and title
plt.xlabel('Year')
plt.ylabel('Grade Point Average GPA')
plt.title('Student Performance')
plt.legend()

# Show the plot
plt.tight_layout()
plt.show()
```

Figure 15: Chat demo involves modifying ***chart editing***. The bar chart is without labeled data points, and all methods provide reasonable and executable drawing code. Qwen-2.5 directly identifies the highest element, while the other two methods make it by code. Note that ChartMoE delivers the most accurate values, thanks to extensive alignment training and proposed MoE architecture.



Instruction

Redraw the chart with python matplotlib, giving the code to highlight data point with lowest growth rate (draw a horizontal dotted line parallel to the x-axi, through the lowest point and add \'lowest\' label in the legend anchor). Please keep the same colors and legend as the input chart.

Table

```
Year,GDP Growth
2010,3.5
2012,4.3
2014,3.8
2016,2.9
2028,3.2
2020,-4.4
2022,5.2
```

Chart

ChartMoE

```
import matplotlib.pyplot as plt
import pandas as pd

# Data: years and corresponding growth rates
data = {'Years': [2010, 2012, 2014, 2016, 2018, 2020, 2022],
'Growth Rate in Percentage': [3.5, 4.3, 3.8, 3.1, 3.2, -4, 5.2]}

df = pd.DataFrame(data)

# Plot the growth rate over the years
plt.plot(df['Years'], df['Growth Rate in Percentage'], \
         label='Growth Rate in Percentage')

# Define the year and value for the lowest point
lowest_point = 2020
lowest_value = -4

# Add a dotted horizontal line for the lowest point
plt.axhline(lowest_value, color='gray', linestyle='dotted', label='Lowest')

plt.text(lowest_point, lowest_value - 0.5, 'Lowest', color='gray')

# Show legend and display the chart
plt.legend()
plt.show()
```

Qwen-2.5

```
import numpy as np
import matplotlib.pyplot as plt

# 假设数据
years = np.array([2010, 2012, 2014, 2016, 2018, 2020, 2022])
growth_rates = np.array([-1.5, 0.5, -2.5, 1.5, -3.5, 4.5])

# 找出最低增长率的索引
min_growth_rate_idx = np.argmin(growth_rates)

# 重新绘制图表
fig, ax = plt.subplots()
ax.plot(years, growth_rates, marker='o', linestyle='--', \
        color='blue', label='Growth Rate in Percentage')
ax.axhline(y=growth_rates[min_growth_rate_idx], xmin=0.1, \
   xmax=0.9, dashes=[5, 5], color='gray', alpha=0.5, zorder=-1)
ax.annotate('lowest', xy=(years[min_growth_rate_idx], \
   growth_rates[min_growth_rate_idx]), xytext=(-10, -10), \
   textcoords='offset points', ha='right', va='bottom', \
   bbox=dict(boxstyle='round', fc='white'))
ax.set_xlabel('Years')
ax.set_ylabel('Growth Rate in Percentage')
ax.set_title('Global GDP Growth')
ax.set_xlim(min(years)-1, max(years)+1)
ax.set_ylim(min(growth_rates)*1.1, max(growth_rates)*1.1)
ax.grid(True)

# 设置图例位置
legend = ax.legend(loc='lower right', shadow=True)
legend.get_frame().set_facecolor('white')
plt.show()
```

GPT-4O

```
# Let's use matplotlib to create a similar chart, and incorporate the requested changes.
import matplotlib.pyplot as plt

# Data for global GDP growth rate
years = [2010, 2012, 2014, 2016, 2018, 2020, 2022]
# Sample data similar to the graph in the image
growth_rate = [3.2, 4.1, 4.5, 3.7, 3.3, -4.3, 5.5]

# Create the plot
plt.figure(figsize=(14,8))
plt.plot(years, growth_rate, label='Growth Rate in Percentage', color='blue', marker='o')

# Highlight the lowest data point
min_growth = min(growth_rate)
min_year = years[growth_rate.index(min_growth)]

# Draw a dotted horizontal line at the lowest growth rate
plt.axhline(y=min_growth, color='red', linestyle='dotted', label='lowest')

# Add chart title and labels
plt.title('Global GDP Growth', fontsize=14)
plt.xlabel('Years', fontsize=12)
plt.ylabel('Growth Rate in Percentage', fontsize=12)

# Add the legend and place it with an anchor
plt.legend(loc='upper right', fontsize=10)

# Display the plot
plt.show()
```

Figure 16: Chat demo involves modifying ***chart editing***. The line chart is without labeled data points, and all methods provide reasonable and executable drawing code. The values extracted by all models differ from the ground truth, but both ChartMoE and GPT-4O captured the correct data trends. Additionally, ChartMoE successfully completed all the editing tasks specified in the instructions.