PLOTCRAFT: PUSHING THE LIMITS OF LLMS FOR COMPLEX AND INTERACTIVE DATA VISUALIZATION

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ABSTRACT

Recent Large Language Models (LLMs) have demonstrated remarkable proficiency in code generation. However, their ability to create complex visualizations for scaled and structured data remains largely unevaluated and underdeveloped. To address this gap, we introduce **PlotCraft**, a new benchmark featuring 1k challenging visualization tasks that cover a wide range of topics, such as finance, scientific research, and sociology. The benchmark is structured around seven high-level visualization tasks and encompasses 48 distinct chart types. Crucially, it is the first to systematically evaluate both single-turn generation and multi-turn refinement across a diverse spectrum of task complexities. Our comprehensive evaluation of 23 leading LLMs on PlotCraft reveals obvious performance deficiencies in handling sophisticated visualization tasks. To bridge this performance gap, we develope **SynthVis-30K**, a large-scale, high-quality dataset of complex visualization code synthesized via a collaborative agent framework. Building upon this dataset, we develope **PlotCraftor**, a novel code generation model that achieves strong capabilities in complex data visualization with a remarkably small size. Across VisEval, PandasPlotBench, and our proposed PlotCraft, PlotCraftor shows performance comparable to that of leading proprietary approaches. Especially, on hard task, Our model achieves over 50% performance improvement. We will release the benchmark, dataset, and code at https://anonymous.4open.science/r/PlotCraft-E320.

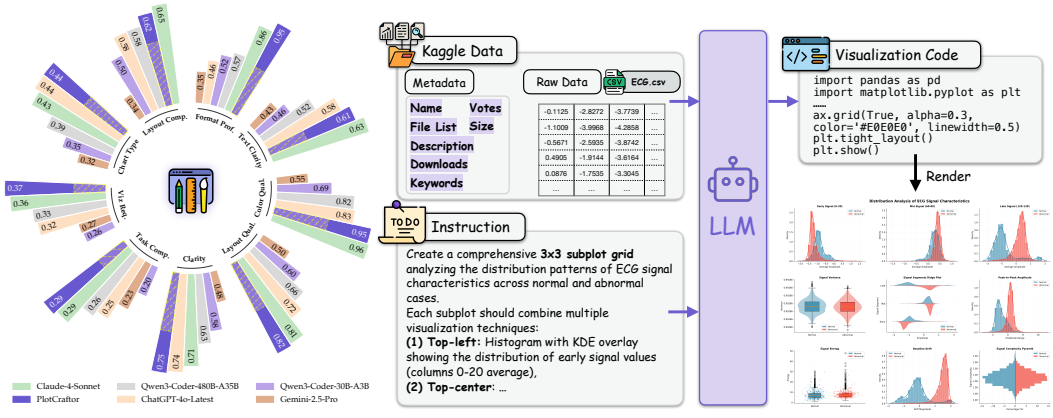

Figure 1: An overview of the PlotCraft benchmark and the performance of several leading LLMs and our model, PlotCraftor. **(Left)** A polar bar chart compares the performance of PlotCraftor against five leading baseline models across all of our proposed sub-metrics. The purple area explicitly highlights the performance gains of PlotCraftor relative to its base model, Qwen3-Coder-30B-A3B. **(Right)** An example task from PlotCraft, which requires an LLM to process raw Kaggle data and a complex, human-written instruction to generate visualization code, which is then rendered into the final chart. PlotCraft benchmark comprises 1k high-quality evaluation instances.

1 INTRODUCTION

Recent advancements in AI research have demonstrated the powerful code generation capabilities of LLMs (OpenAI, 2023; 2025; Anthropic, 2023; Team, 2024; Rozière et al., 2023; Hui et al., 2024; MistralAI, 2024; Team et al., 2025b), which have solved coding challenges in domains such as software engineering (Jimenez et al., 2023; Zhang et al., 2025; Pan et al., 2025b), code completion Ding et al. (2023); Yang et al. (2024a); Gong et al. (2024), and algorithmic problem-solving (Chen et al., 2021a; Zhuo et al., 2025; Jain et al., 2024). However, in the domain of data visualization, the capabilities of LLM have yet to be fully explored. We observe that while LLMs excel at creating simple, single-panel charts, they struggle to generate plots with multiple subplots and intricate composite layouts from large, complex structured data. As illustrated in **Figure 2**, when faced with these complex plotting tasks, LLMs often generate code that results in chaotic layouts, overlapping elements, and obscured axis labels, or they completely ignore instructions about certain areas of plots.

Prior works on chart generation have primarily focused on relatively simple, text to visualization (Text2Vis) tasks (e.g., VisEval (Chen et al., 2024)/PandasPlotBench (Galimzyanov et al., 2025)) or on understanding and reproducing existing data charts (Chart2Code) (e.g., Plot2Code (Wu et al., 2024), ChartMimic (Yang et al., 2025b)). However, these efforts do not adequately assess the ability of LLMs to synthesize complex visualization code from structured raw data. To systematically evaluate these capabilities of LLMs, we introduce **PlotCraft**, a large-scale benchmark comprising 982 instances. PlotCraft is characterized by its use of instructional prompts of varying difficulties, a diverse range of chart types, and multi-level evaluation metrics. Specifically, we design and collect tasks of varying difficulty based on the number of subplots to be generated, chart complexity, data volume, and the level of detail in the instructions. Furthermore, we introduce an additional multi-turn refinement task, which allows the model to refine the chart over multiple conversational turns, thereby assessing its ability to debug code and perform iterative optimization based on user feedback. **Figure 1** provides an overview of our benchmark.

We evaluate 23 prominent LLMs on PlotCraft benchmark, including 6 proprietary models and 17 open-weight models. We observe that most models perform well on simple chart generation tasks, but fail on medium and hard tasks, which require processing larger data and generating composite plots with multiple, properly arranged chart types. Results show that existing LLMs have limited capabilities in complex scientific visualization code generation tasks. To further validate our findings, we score a set of results with human evaluation and a correlation analysis **(Section 5.3)** demonstrates a high correlation between our multi-level metrics and human evaluation.

To address the limited visualization code generation capabilities, we constructe a new dataset **SynthVis-30K**, and a novel model **PlotCraftor**. Specifically, we collect 30k multi-modal chart data instances covering 31 topics, 48 chart types, and 7 tasks. Each data instance contains a human instruction, some data files for visualization (CSV/XLSX), the resulting chart image, and the corresponding source code. A detailed breakdown of the dataset's coverage and the curation pipeline is presented in Figure 3. Based on SynthVis-30K, we construct PlotCraftor that achieves strong capabilities in complex data visualization with a minimal model size.

Experimental results demonstrate that PlotCraftor improves performance on PlotCraft by 25%, achieving performance comparable to leading proprietary LLMs. Concurrently, we adapt other benchmarks to our task settings, including VisEval (Chen et al., 2024), PandasPlotBench (Galimzyanov et al., 2025). PlotCraftor demonstrate a 7% higher performance compared to the much larger Qwen3-Coder-480B. These results validate PlotCraftor's powerful abilities in different text-to-visualization code generation tasks.

2 RELATED WORKS

2.1 CODE GENERATION

Recent advances in Large Language Models (LLMs), including general-purpose models (e.g., GPT (OpenAI, 2023), Claude (Anthropic, 2023), Gemini (Team, 2024)) and specialized code models (e.g., Qwen-Coder (Hui et al., 2024), DeepSeek-Coder (Guo et al., 2024), Codestral (MistralAI, 2024)), have demonstrated powerful coding capabilities (DeepSeek-AI & etc., 2024; Rozière et al., 2023; Team et al., 2025b;a). While conventional tasks like algorithmic problem-solving (Chen et al.,

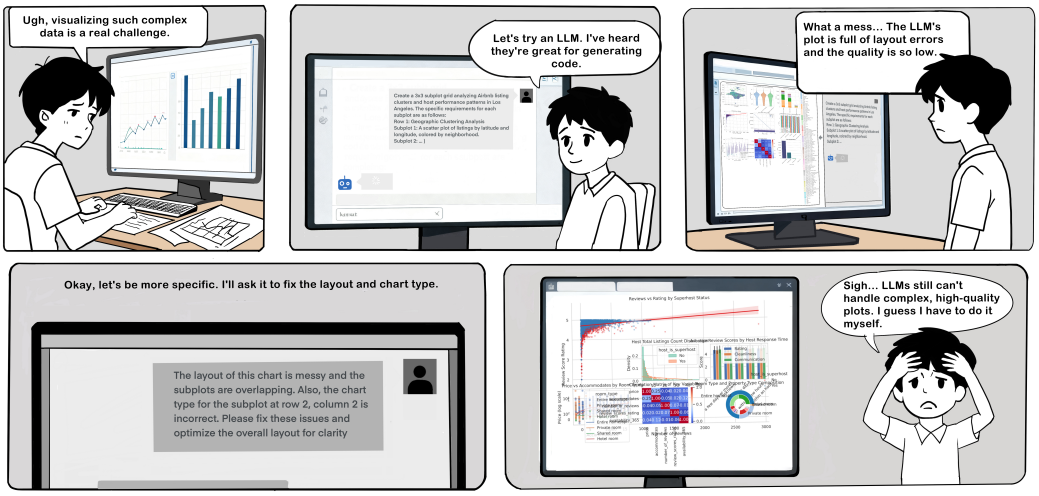

Figure 2: A real-world example illustrating the limitations of LLMs on complex visualization tasks. When presented with a sophisticated request, the model generates a low-quality output and struggles to make effective improvements during the subsequent refinement process.

2021a; Zhuo et al., 2025) and software engineering (Jimenez et al., 2023; Zhang et al., 2025) are evaluated on functional correctness (Chen et al., 2021b), this paper focuses on data visualization, a domain where generated code must produce a visually accurate output, a requirement shared by front-end design (Xu et al., 2025; Lu et al., 2025) and SVG generation (Xing et al., 2025).

2.2 Data Visualization

Prior LLM-based data visualization research spans three areas: The first, chart understanding (e.g., QA and captioning), focuses on interpreting visual information from plots, such as for question answering or summary generation (Li et al., 2024; Zeng et al., 2024; Rahman et al., 2023; Kantharaj et al., 2022; Jia et al., 2025). The second, Chart-to-Code (Chart2Code) generation, involves reverse-engineering a visualization by generating the code required to replicate it (Wu et al., 2024; Yang et al., 2025b; Zhao et al., 2025), and the third, Text-to-Visualization (Text2Vis), concerns generating visualization specifications or code from natural language descriptions (Luo et al., 2025; Galimzyanov et al., 2025; Ni et al., 2025). However, these works predominantly focus on simple, single-panel plots, offering limited differentiation for advanced LLMs' ability to handle complex layouts and high information density. We introduce PlotCraft to address this critical evaluation gap.

3 The PlotCraft Benchmark

3.1 Task Definition

We define the data visualization task as a conditional code generation problem. Formally, given a natural language instruction I, metadata M, and a raw dataset D, a Large Language Model ($\mathcal{F}$) must generate an executable code snippet C. This code must use D to render a visualization that satisfies all requirements outlined in I. This task is formulated as $C = \mathcal{F}(I, M, D)$. The PlotCraft benchmark evaluates models on two distinct variants of this core task.

The two variants are: **(1) Single-Turn Generation**, where the model must generate the complete visualization code in a single step from the initial instruction, thereby measuring its ability to execute complex requests from scratch; and **(2) Multi-Turn Refinement**, which assesses a model's ability to debug and iteratively improve existing code based on a conversation history and a new modification request, mirroring a realistic user interaction workflow.

3.2 Benchmark Coverage Analysis

The PlotCraft benchmark comprises 982 evaluation instances, evenly divided into 491 for single-turn generation and 491 for multi-turn refinement. Both single-turn and multi-turn tasks are based on the

Table 1: A comparison of PlotCraft with existing benchmarks. A ✓indicates the presence of a feature, while a ✗indicates its absence.

Benchmarks	# of Test Instances	Composite Types	Multiple Subplots	Multi-Turn	Evaluation Metric
Chart Understanding Benchmarks					
ChartQA (Masry et al., 2022)	10K	✗	✗	✗	Accuracy
ChartSumm (Rahman et al., 2023)	84K	✗	✗	✗	Match-based
CharArXiv (Wang et al., 2024)	93K	✗	✓	✗	MLLM Score
ChartX (Xia et al., 2025)	1152	✓	✗	✗	Multi-Level
Chart to Code Benchmarks					
Plot2Code (Wu et al., 2024)	132	✗	✓	✗	MLLM Score
Design2Code (Si et al., 2024)	484	✗	✗	✗	Multi-Level
ChartMimic (Yang et al., 2025b)	4,800	✓	✓	✗	Multi-Level
Text to Visualization Benchmarks					
MatPlotBench Yang et al. (2024b)	100	✗	✗	✗	MLLM Score
VisEval Chen et al. (2024)	2300	✗	✗	✗	Multi-Level
PandasPlotBench Galimzyanov et al. (2025)	150	✗	✗	✗	Multi-Level
PlotCraft (Ours)	982	✓	✓	✓	Multi-Level

same underlying visualization goal. We describe the benchmark's coverage across three dimensions: Chart Types, Thematic Topics, and Task Complexity (the same as shown in Figure 3).

Chart Types Tasks in PlotCraft are categorized according to a high-level Visualization Intent Taxonomy, encompassing seven primary classes: Correlation, Deviation, Ranking, Distribution, Composition, Change, and Groups. These categories contain 48 distinct plot types, including scatter plots, bubble plots, pie charts, dendrograms, violin plots, and so on. As the majority of tasks require the combination of multiple plot types within a single figure, a single, exclusive plot type label is often not applicable. We provide illustrative examples for each category in Appendix A.1.

Thematic Coverage PlotCraft spans a diverse range of thematic topics to ensure broad applicability. The benchmark is organized into eight high-level domains: Finance (Business & Finance), Industry (Industry & E-commerce), Health (Health & Medicine), Research (Science & Research), Society (Government & Society), Media (Culture & Media), Tech. (Technology & Computing), and Env. (Environment & Geospatial). These domains are further divided into 31 fine-grained sub-topics, a detailed breakdown of which is provided in Appendix A.2.

Task Complexity To systematically evaluate model capabilities, tasks are stratified into three levels of complexity: (1) Easy: The task requires generating a single, standard chart (e.g., a bar chart or a line plot) to visualize the data. (2) Medium: The task involves creating a composite visualization, which could be either a single chart combining multiple plot types or a subplot grid where each individual subplot is of a simple nature. (3) Hard: The task demands the creation of a complex subplot grid where each individual subplot is itself a composite chart, requiring advanced spatial and logical reasoning. We provide illustrative examples for different complexity in Appendix A.3.

3.3 Data Curation Process

The construction of PlotCraft adheres to four guiding principles: (1) Grounded in Real Data: All tasks are based on real-world datasets to avoid artifacts of synthetic data. (2) Built from Scratch: All tasks and reference solutions are newly created to prevent data leakage from existing sources. (3) Zero-Reference Generation: Tasks provide no sample images or code, requiring models to generate visuals from abstract instructions. (4) Compositional Complexity: The benchmark spans a wide spectrum of complexities, including tasks with intricate layouts and multiple chart types within a single figure. Adhering to these principles, we curate the benchmark through a four-step pipeline, which we overview here. Further details are provided in Appendix B.

Data Filtering We source open-source datasets from Kaggle. The use of these datasets in our work is for scientific research purposes only; other uses are subject to their original licenses. Using metrics such as vote counts, download counts, and usability ratings, we performed an initial screening of 7,162 datasets, comprising over 95,000 files and 25.6 billion data rows. From this pool, we conduct a second filtering stage to select 140 core datasets for the benchmark. This selection was curated to ensure diverse topics, a wide distribution of data volume and complexity, and minimal overlap with datasets used in other visualization tasks to mitigate data leakage. The final collection of benchmark datasets contains 1,874 raw data files and approximately 462 million data rows.

Task and Instruction Writing Using the selected benchmark datasets, we authored 491 unique visualization tasks. The design of these tasks was guided by a combination of seven high-level visualization intents and 48 distinct chart types. We ensure a roughly balanced distribution of tasks across three complexity levels: simple (159), medium (163), and hard (169). The accompanying instructions are written to be abstract, specifying only the visualization requirements without providing any guidance on code implementation.

Reference Code Writing For each task, a reference solution is implemented by a team of five senior Python developers using Matplotlib and its associated libraries. It is important to note that this code serves as a valid reference implementation that achieves a high-quality result, rather than the single, optimal solution. The details of the sandboxed execution environment used for our evaluation are provided in Appendix A.4.

Multi-turn Conversation Synthesis To simulate realistic refinement scenarios, we first generate an initial code draft for each task using a less capable model. Human experts then review these drafts and intentionally introduced common, realistic errors—such as incorrect chart types or overlapping visual components—to create a faulty, low-quality implementation. Examples of such faulty code are provided in Appendix B.4. This faulty code, along with its rendered image and the original instruction, was presented to human annotators who then wrote a natural language modification request to correct the errors. Each multi-turn task instance is thus composed of the original instruction, data metadata, the faulty code, and this human-authored refinement prompt. This process yield 491 multi-turn tasks, which, combined with the 491 single-turn tasks, constitute the complete PlotCraft benchmark of 982 instances.

3.4 Evaluation Metrics

Our evaluation pipeline first assesses functional correctness. All generated code must execute successfully in our sandboxed environment and produce a valid, non-empty image to be eligible for further analysis. Any code that fails this initial step receives a score of zero. For all valid outputs, we follow established practices and employ Gemini-2.5-Pro as an automated visual judge. We acknowledge that relying on an automated judge, especially a proprietary model, introduces inherent limitations and potential biases in visual and aesthetic judgment (Xie et al., 2025; Pan et al., 2025a; Shi et al., 2025). This judge scores the generated charts based on a two-dimensional framework: **Task Compliance** and **Chart Quality**. To ensure a granular assessment, Task Compliance is decomposed into four distinct sub-metrics evaluated on a binary scale (0=fail, 1=pass): Layout Compliance, Chart Type Compliance, Requirement Fulfillment, and Complete Task Fulfillment. Similarly, Chart Quality is assessed on a 3-point scale (0, 1, or 2) across five criteria: Clarity (the absence of overlapping elements), Layout Quality, Color Quality, Text Readability, and Professional Formatting. The detailed scoring rubrics for all metrics, along with the specific prompts used to query our automated judge and specific judgement cases, are available in Appendix C.

4 The PlotCraftor

To address the performance gap observed in our benchmark evaluations, we develope PlotCraftor, a model specifically fine-tuned for complex data visualization. The development process consists of two key stages: the creation of a large-scale, high-quality synthetic dataset, which we call SynthVis-30K, and the subsequent Supervised Fine-Tuning (SFT) of a base model on this data.

4.1 SynthVis-30K Dataset

The SynthVis-30K dataset was created using a multi-agent framework, illustrated in Figure 3, which comprises two main stages: **Task Generation** and **Code Generation**. Details are in Appendix E.

Task Generation. We first sourced a collection of Kaggle datasets (with CC BY 4.0 or Apache 2.0 licenses), ensuring no overlap with those used in the PlotCraft benchmark to prevent data contamination. A Data Analyzer agent processes each dataset to extract structured metadata, including data types, column names, and sample rows. This formatted data then enters a Task Cycle, an iterative loop between a Task Generator and a Task Judge. The Task Generator, prompted with few-shot examples from PlotCraft, proposes 3-6 visualization tasks of varying difficulty for a given dataset. The

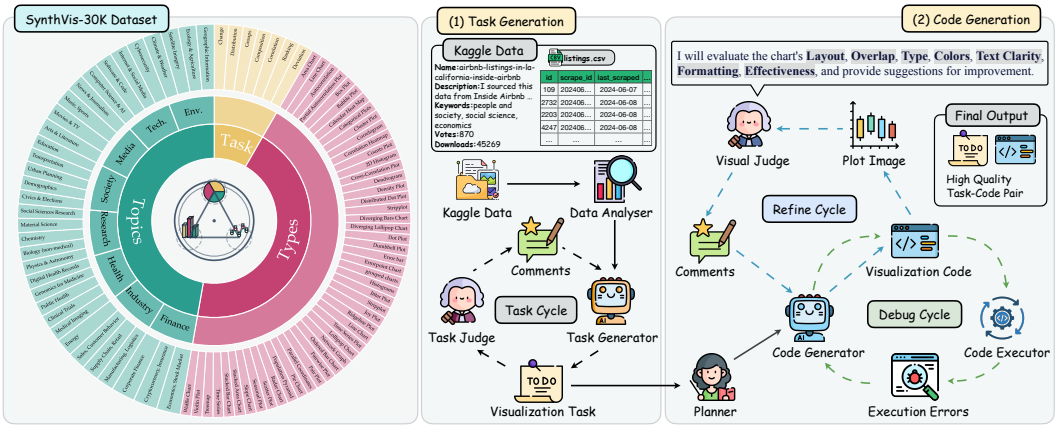

Figure 3: An overview of the SynthVis-30K dataset, detailing its coverage and the multi-agent framework used for its creation. **(Left)** A hierarchical chart illustrates the dataset's comprehensive coverage across three dimensions: thematic Topics, chart Types, and visualization Tasks. **(Right)** A schematic of our multi-agent data synthesis pipeline. This framework consists of two primary stages, Task Generation and Code Generation, which process raw Kaggle data to produce complete, multi-modal visualization instances. Each instance comprises structured data, a natural language instruction, the visualization code, and the corresponding rendered image.

Task Judge assesses these tasks for feasibility and coherence, providing feedback for refinement. This cycle repeats until a high-quality visualization task is finalized.

Code Generation. The generated task is then passed to a Planner agent, which creates a high-level plan for implementation. Following this plan, a Code Generator agent produces the visualization code through two iterative feedback loops: a Debug Cycle and a Refine Cycle. In the Debug Cycle, the code is passed to an Executor—a sandboxed Python environment (Appendix A.4). If the code fails, the resulting error message is returned to the Code Generator for debugging until the code is executable. Subsequently, in the Refine Cycle, the error-free code is used to render an image. A Visual Judge evaluates this image on multiple criteria (Layout, Overlap, Type, Colors, Text Clarity, Formatting, and Effectiveness) and provides natural language feedback. The Code Generator refines the code based on this feedback. These cycles continue until the code is both executable and produces a high-quality visual, resulting in a final task-code pair.

SFT Trajectory Synthesis. Finally, we convert the curated task-code pairs into training instances for SFT. For single-turn data, we use an external LLM (Claude) to generate a concise Chain-of-Thought (CoT) rationale that explains the steps from the task instruction to the final code. The instruction, CoT, and code are then combined into a single-turn training trajectory. For multi-turn data, we extract high-quality interactions from the Refine Cycle logs, specifically selecting instances where the Visual Judge's feedback led to a significant improvement in the code's quality score. These successful interactions form our multi-turn refinement trajectories.

4.2 Model Training

We develope PlotCraftor by Supervised Fine-Tuning (SFT) on the Qwen3-Coder-30B-A3B model using our SynthVis-30K dataset. The training is configured with a context length of 131,072 tokens and proceeded for 3 epochs. We use a global batch size of 64 and a micro-batch size of 1. The learning rate is 7×10^{-6}, which include a warm-up phase of 30 steps. The learning rate is subsequently decreased via a linear decay schedule to a minimum of 7×10^{-7}. We utilize BF16 for mixed-precision training to enhance efficiency. All training leverage the Megatron-LM framework (Shoeybi et al., 2020).

Table 2: **Quantitative results on PlotCraft for 16 primary LLMs across two settings: Single-Turn Generation and Multi-Turn Refinement.** Task-Comp. and Quality denote the total scores for the Task Compliance (out of a maximum of 4) and Chart Quality (out of a maximum of 10) sub-metrics, respectively. AVG score is the average of these scores across both single-turn and multi-turn evaluations. Within each model category, the best score is **bolded** and the second-best is underlined.

Model	Single-Turn Generation			Multi-Turn Refinement			AVG score
	Pass Rate (%)	Task-Comp.	Quality	Pass Rate (%)	Task-Comp.	Quality	
Closed-source LLMs							
Claude-4.1-Opus (Anthropic, 2023)	**76.20**	**1.93**	**4.20**	**81.44**	**2.05**	**5.22**	**6.70**
Claude-4-Sonnet (Anthropic, 2023)	68.84	1.73	3.99	78.41	1.88	4.80	6.20
Gemini-2.5-Pro (Team, 2024)	41.34	1.15	2.31	58.86	1.51	3.80	4.39
ChatGPT-4o-Latest (OpenAI, 2023)	63.54	1.60	3.33	69.25	1.51	4.23	5.33
GPT-5 (OpenAI, 2025)	69.86	1.76	2.87	74.13	1.80	4.33	5.38
Grok-4 (xAI, 2025)	64.52	1.63	3.66	70.24	1.61	4.42	5.65
Open-source LLMs							
Kimi-K2 (Team et al., 2025b)	60.13	1.52	3.36	61.03	1.49	4.05	5.21
DeepSeek-V3.1 (DeepSeek-AI & etc., 2024)	55.71	1.49	3.20	56.86	1.50	3.99	5.09
GLM-4.5 (Team et al., 2025a)	43.38	1.25	2.48	64.97	1.54	3.91	4.59
GPT-oss-120B (Agarwal et al., 2025)	48.23	1.32	2.68	29.69	0.77	1.87	3.32
GPT-oss-20B (Agarwal et al., 2025)	44.68	1.21	2.43	34.02	0.89	2.14	3.34
Seed-Coder-8B (Seed et al., 2025)	32.38	0.87	1.74	57.03	1.26	3.22	3.55
VisCoder-7B (Ni et al., 2025)	25.46	0.67	1.50	51.73	0.99	2.96	3.06
Qwen3-Coder-480B-A35B (Hui et al., 2024)	61.30	1.56	3.21	75.97	1.75	4.46	5.49
Qwen3-Coder-30B-A3B (Hui et al., 2024)	52.55	1.32	2.85	73.12	1.55	4.18	4.95
PlotCraftor-30B-A3B (Ours)	**64.36**	**1.73**	**4.09**	**77.11**	**1.76**	**4.74**	**6.16**

Table 3: Quantitative results for 16 LLMs across two benchmarks, VisEval and PandasPlotBench.

Model	VisEval					PandasPlotBench		
	Invalid Rate (%)	Illegal Rate (%)	Pass Rate (%)	Readability	Quality	Pass Rate (%)	Vis	Task
Closed-source LLMs								
Claude-4.1-Opus (Anthropic, 2023)	**0.87**	**5.42**	**96.14**	**4.39**	**3.91**	**100**	**78**	**95**
Claude-4-Sonnet (Anthropic, 2023)	1.82	6.78	94.51	4.27	3.85	98.3	75	92
Gemini-2.5-Pro (Team, 2024)	6.79	15.83	83.71	3.76	3.09	85.1	66	77
ChatGPT-4o-Latest (OpenAI, 2023)	3.39	14.54	84.47	4.01	3.34	93.7	72	89
GPT-5 (OpenAI, 2025)	5.01	12.98	87.71	4.22	3.52	82.9	66	79
Grok-4 (xAI, 2025)	4.02	8.53	94.41	4.30	3.69	94.6	75	88
Open-source LLMs								
Kimi-K2 (Team et al., 2025b)	**2.45**	**8.91**	93.62	4.24	3.78	95.4	**76**	**91**
DeepSeek-V3.1 (DeepSeek-AI & etc., 2024)	5.94	9.82	92.31	4.17	3.59	93.7	74	86
GLM-4.5 (Team et al., 2025a)	5.03	13.07	88.54	4.19	3.48	47.4	39	44
GPT-oss-120B (Agarwal et al., 2025)	3.91	14.88	90.13	4.03	3.35	92.6	71	88
GPT-oss-20B (Agarwal et al., 2025)	5.23	15.12	86.34	3.95	3.28	85.7	69	87
Seed-Coder-8B (Seed et al., 2025)	8.15	18.25	75.40	3.45	2.81	54.3	65	80
VisCoder-7B (Ni et al., 2025)	6.45	16.05	82.88	3.81	3.12	87.7	66	78
Qwen3-Coder-480B-A35B (Hui et al., 2024)	2.89	11.53	91.75	4.18	3.55	**97.1**	73	87
Qwen3-Coder-30B-A3B (Hui et al., 2024)	3.55	13.90	89.67	4.10	3.41	94.3	71	86
PlotCraftor-30B-A3B (ours)	2.61	9.76	**93.81**	**4.26**	**3.80**	96.0	74	**91**

5 EXPERIMENTS

5.1 EXPERIMENTS SETUP

Baseline Setup We evaluate a total of 24 models, including our proposed **PlotCraftor** and 23 widely-used proprietary and open-source Large Language Models. For proprietary models, we select six representative systems: Anthropic's flagship models, Claude-4.1-Opus and Claude-4-Sonnet (Anthropic, 2023); OpenAI's most advanced models, GPT-5 and GPT-4o (latest version) (OpenAI, 2025); Google's Gemini 2.5 Pro (Team, 2024); and xAI's Grok-4 (xAI, 2025). For open-weight models, we choose nine competitive models with parameter sizes ranging from 7B to 1T: Kimi-K2 (Team et al., 2025b) (1T, A32B), Deepseek-V3.1 (DeepSeek-AI & etc., 2024) (671B, A37B), GLM-4.5 (Team et al., 2025a) (355B, A32B), GPT-oss (Agarwal et al., 2025) (120B, A5.1B; 20B, A3.6B), Qwen3-Coder (Hui et al., 2024) (480B, A22B; 30B, A3B), Qwen2.5-Coder (Hui et al., 2024), DeepSeek-Coder (Guo et al., 2024), and Qwen3 (Yang et al., 2025a). Additionally, we include Seed-Coder-8B (Seed et al., 2025) and Viscoder-7B (Ni et al., 2025) as baseline models of a comparable size to our PlotCraftor (30B, A3B) for a more direct comparison.

Benchmark Setup To ensure a comprehensive evaluation, in addition to our primary PlotCraft benchmark, we assessed model performance on two other established text2vis benchmarks. The first, VisEval (Chen et al., 2024), is a large-scale benchmark composed of high-quality visualization

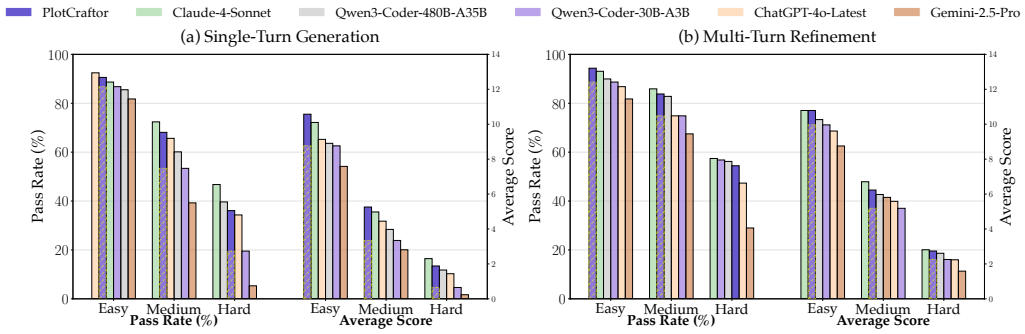

Figure 4: Performance comparison of PlotCraftor and five leading LLMs on tasks of varying difficulty. The figure is split into two subplots: **(a)** Single-Turn Generation and **(b)** Multi-Turn Refinement. Within each subplot, we report the Pass Rate (%) and Average Score for tasks categorized as Easy, Medium, and Hard. The yellow hatched area within the PlotCraftor bars indicates the score contribution from its base model, Qwen3-Coder-30B-A3B.

tasks curated from nvBench (Luo et al., 2025). It employs a multi-faceted evaluation protocol that includes execution pass rate, GPT-4 based scoring, and SVG based layout checks. The second, PandasPlotBench (Galimzyanov et al., 2025), is a benchmark containing 175 test cases specifically designed to evaluate code generation for Matplotlib and its related libraries.

Evaluation Details All experiments were conducted by sending requests in the standard OpenAI API format, with the chat structure following the ChatML format (OpenAI, 2022). We employed a greedy decoding strategy and set the maximum output length to 131,072 tokens; if a model did not support this length, we used its specified maximum limit. The final reported results are the average of three experimental runs. For proprietary models, we queried their official APIs directly. For open-weight models, we utilized the vLLM framework for serving. It is important to note a potential limitation regarding the GPT-oss series of models: as they are trained on the harmony format (Agarwal et al., 2025), which natively incorporates multi-turn reasoning and tool invocation, our standardized ChatML-based setup may not fully leverage their intended capabilities. Additional evaluation details and specific prompts are in Appendix F.

5.2 Main Results

This section presents the results of 16 leading LLMs on the PlotCraft, VisEval, and PandasPlotBench benchmarks. Performance on PlotCraft is detailed in Table 2, with complete 24 models results available in Appendix Table 7. Results for VisEval and PandasPlotBench are shown in Table 3. For a granular analysis, Figures 1 and 4 break down performance by sub-metrics and task difficulty, respectively. The key findings are as follows.

Claude-4.1-Opus leads proprietary models, while PlotCraftor is the top-performing open-weight model, achieving results comparable to Claude-4-Sonnet. Among proprietary models, Claude-4.1-Opus demonstrates a significant advantage across all tasks. It achieved an average score of 6.70 on PlotCraft and a perfect 100% pass rate on PandasPlotBench, substantially outperforming other models.

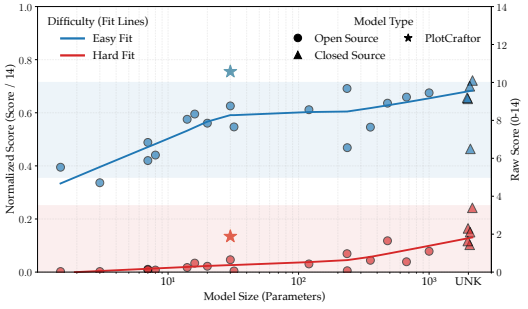

Figure 5: Performance scaling on Easy vs. Hard.

Among open-weight models, our PlotCraftor achieves SOTA performance on PlotCraft. It surpasses its base model, Qwen3-Coder-30B-A3B, by a margin of 25% and nearly matches the performance of the top-tier Claude 4 Sonnet, with a score difference of less than 1%. PlotCraftor also secures leading results among open models on the VisEval and PandasPlotBench benchmarks. An analysis of performance by task difficulty, focusing on 6 key models (4 widely-used coding

Table 4: Cohen's Kappa scores for agreement between our Gemini-2.5-Pro judge and human evaluations, categorized by Compliance and Quality metrics.

Compliance Metrics				Quality Metrics				
Layout	Type	Visual	Task	Clarity	Layout	Color	Text	Format
0.90	0.78	0.72	0.80	0.73	0.71	0.69	0.65	0.73

models, our baseline, and PlotCraftor), reveals that while GPT-4o excels on simple, single-turn tasks, Claude 4.1 Opus shows superior performance on more complex and demanding tasks. A more detailed discussion and comparison between different models is available in Appendix G.

Strong performance on simple benchmarks does not guarantee success on complex visualization tasks. We observe a significant performance disparity between models on different benchmarks. Models such as Kimi-K2 and GPT-4o, which perform exceptionally well on the simpler tasks found in VisEval and PandasPlotBench, experience a notable performance degradation on the complex, multi-faceted tasks within PlotCraft. In contrast, the Claude series and our PlotCraftor demonstrate consistently high performance across all three benchmarks, indicating their robust capability in handling both simple and sophisticated visualization challenges.

Task difficulty significantly impacts the effectiveness of model scaling and fine-tuning. As shown in Figure 5, the benefits of model scaling are highly dependent on task difficulty. For models under 100B parameters, performance on Easy tasks scales rapidly with size, while performance on Hard tasks remains flat, only improving for models beyond the 100B threshold. This disparity is mirrored in supervised fine-tuning (SFT): smaller models can be fine-tuned to near-proprietary levels on Easy tasks, yet SFT provides minimal benefit for Hard tasks. This indicates that solving complex visualization challenges may rely more on the emergent reasoning abilities that come with scale than on task-specific fine-tuning.

5.3 Correlation with Human Evaluation

To validate the reliability of our proposed multi-dimensional metrics, we measured their correlation with human expert judgments. We conducted a scoring experiment on 500 charts randomly sampled from the output of PlotCraftor. For each chart, three human annotators provided scores for all metrics, with the final ground-truth score determined by a majority vote. We then calculated the Cohen's Kappa coefficient to assess the inter-rater agreement between these human-derived scores and the automated scores provided by our Gemini-2.5-Pro based judge. As presented in Table 4, the average Kappa score across all evaluation metrics reached a substantial level of agreement, demonstrating the reliability of our automated evaluation framework. A comparative analysis of other models as evaluators is detailed in Appendix H, where we found that models such as Claude and GPT-4o were significantly less effective at replicating human scoring patterns.

5.4 Error Analysis

To understand the primary failure modes on the PlotCraft benchmark, we analyzed common errors and categorized them into three main types. **(1) Code-Level Errors**, includes functionally flawed code that causes runtime exceptions or critical rendering failures, such as using non-existent object attributes or creating conflicts between incompatible layout managers (e.g., `constrained_layout` with `fig.legend()`). **(2) Task Compliance Failures**, occurs when the visual output disregards explicit instructions, such as generating an incorrect subplot layout or using the wrong chart types. **(3) Deficiencies in Chart Quality**, refers to aesthetic issues that degrade the visualization's readability and professional appearance, including element overlap, suboptimal color choices, and incorrect text. A more detailed, case-by-case analysis of these errors is provided in Appendix I.

6 Conclusion and Future Direction

In this work, we addressed the significant gap in the ability of Large Language Models to handle complex data visualization. We introduced PlotCraft, a novel and challenging benchmark designed to evaluate both single-turn generation and multi-turn refinement capabilities. Our comprehensive evaluation over 23 leading models on PlotCraft demonstrated that current LLMs struggle with sophisticated visualization tasks. To bridge this performance gap, we developed the SynthVis-30K dataset and used it to train PlotCraftor, a novel and efficient model. Experimental results show that PlotCraftor achieves state-of-the-art performance among open-weight models, delivering results comparable to leading proprietary LLMs. Meanwhile, we observed that there are still limitations in data generation and evaluation. The synthesis of high-quality data relies on costly multi-agent systems, and MLLM-based judges may fail to detect subtle visual errors, like minor overlaps or color style. This might be an area for future research. Furthermore, while PlotCraft focuses on detailed instructions to rigorously test capability limits, exploring model performance under abstract or open-ended goals remains a promising direction for future work.

7 Ethics Statement

The data used in the PlotCraft benchmark is sourced exclusively from public repositories that are governed by licenses permitting their use in software and research. Our contributions fully adhere to the terms of these licenses. We did not use any data beyond what is publicly available and downloadable via the standard Kaggle API. Our work did not involve the participation of any human subjects; we did not use crowdsourcing or recruit any external human workers for any part of the PlotCraft benchmark's creation. All work, including the environment configuration, data curation, synthetic data generation, and the writing of this paper, was conducted entirely by the author team.

8 Reproducibility Statement

To ensure the reproducibility of our work, we provide a complete codebase with detailed instructions for replicating the PlotCraft benchmark results and the PlotCraftor training process. The evaluation framework for PlotCraft is described in Section 3.4, with the full scoring rubrics and judge prompts available in Appendix C. The training methodology and hyperparameters for PlotCraftor are detailed in Section 4.2, with additional specifics on the SynthVis-30K data synthesis process provided in Appendix E. The complete specifications of our sandboxed execution environment are detailed in Appendix A.4. To further facilitate community engagement and standardized evaluation, we plan to release a PyPI package and host a public leaderboard for the benchmark.

9 LLM Usage

The use of Large Language Models (LLMs) in this work was limited. A multimodal large model was employed to generate the layout for some of the images shown within the monitor displays in Figure 2. Additionally, an LLM was used sparingly for writing assistance.

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APPENDIX

A BENCHMARK COVERAGE DETAILS

This section provides a detailed breakdown of the PlotCraft benchmark's coverage. Table 5 presents the frequency distribution of 48 distinct chart types as they are mentioned within the instructions for each visualization task in the PlotCraft dataset. This distribution highlights the diversity of chart creation tasks included in the benchmark.

Table 5: This table illustrates the frequency distribution of 48 chart types mentioned within the instructions of visualization tasks from the PlotCraft dataset. To prevent data skew from repetition, each distinct task was analyzed and counted a single time, given that the same set of tasks is utilized for both single-turn and multi-turn interactions.

Type	Count	Type	Count	Type	Count	Type	Count
Line Chart	279	Scatter Plot	225	Time Series	179	Area Chart	164
Correlation Heatmap	145	Violin Plot	132	Box Plot	130	Stacked Area Chart	127
Error bar	96	Bubble Plot	91	Time Series Plot	88	Density Plot	85
Stacked Bar Chart	79	Network Graph	75	Parallel Coordinates	71	Histograms	70
Pie Chart	68	Radar Chart	67	grouped charts	67	Counts Plot	57
Dendrogram	56	Slope Chart	56	Seasonal Plot	54	Treemap	54
Cluster Plot	44	Population Pyramid	24	Pair Plot	17	Lollipop Chart	15
Dumbbell Plot	14	Autocorrelation	10	Cross-Correlation Plot	9	Waffle Chart	9
2D Histogram	7	Diverging Lollipop Chart	7	Pairwise Plot	7	Dot Plot	6
Jitter Plot	6	Partial Autocorrelation Plot	6	Categorical Plots	4	Joy Plot	4
Diverging Bars Chart	3	Ridgeline Plot	2	Stripplot	2	Calendar Heat Map	1
Correlogram	1	Distributed Dot Plot	1	Errorpoint Chart	1	Ordered Bar Chart	1

A.1 CHART TYPES

Distribution Tasks in this category require the visualization of data spread and grouping. Figure 6 presents a representative example of a class distribution task. The associated instruction demands the generation of a complex, multi-panel figure: "Create a comprehensive 3x3 subplot grid analyzing the distribution patterns of ECG signal characteristics across normal and abnormal cases."

Correlation This category focuses on tasks that require visualizing the relationship and interdependence between two or more variables. Figure 7 illustrates a representative example, for which the model must generate a complex multi-panel visualization. The instruction for this task is: "Create a comprehensive 3x3 subplot grid analyzing the relationship between economic indicators and Olympic performance across different regions."

Groups This category involves tasks that require visualizing clusters, hierarchies, and other logical groupings within a dataset. Figure 8 shows a complex example where the model is instructed to represent intricate relationships with the prompt: "Create a comprehensive 3x3 subplot grid analyzing the clustering patterns and hierarchical relationships within the Brawl Stars competitive ecosystem."

Change Tasks in the Change category focus on visualizing trends, time-series data, and the evolution of metrics over a period. A representative example is presented in Figure 9, where the instruction requires a multi-faceted temporal analysis: "Create a comprehensive 3x2 subplot grid analyzing the temporal evolution of NIRF rankings across different educational categories from 2016-2021."

Composition This category requires visualizing the composition of a whole, illustrating the proportions and breakdown of its constituent parts. Figure 10 provides an example of a multi-dimensional composition task, with the instruction: "Create a composite visualization showing Netflix content composition across different dimensions, designed as a 2x2 subplot grid."

Ranking Ranking tasks involve comparing and ordering items based on one or more quantitative metrics. Figure 11 showcases an example where the model is prompted to perform a comparative ranking with the instruction: "Create a comprehensive ranking visualization that compares Udemy course performance across different metrics. Design a 2x2 subplot grid."

TO DO

Example 1 - Distribution

Instruction

Create a comprehensive 3x3 subplot grid analyzing the distribution patterns of ECG signal characteristics across normal and abnormal cases. Each subplot should combine multiple visualization techniques: (1) Top-left: Histogram with KDE overlay showing the distribution of early signal values (columns 0-20 average), (2) Top-center: Histogram with KDE overlay for mid-signal values (columns 60-80 average), (3) Top-right: Histogram with KDE overlay for late signal values (columns 120-139 average), (4) Middle-left: Box plot with violin plot overlay comparing signal variance across normal vs abnormal cases, (5) Middle-center: Ridge plot showing signal amplitude distributions at different time segments (early, mid, late) for both classes, (6) Middle-right: Histogram with KDE overlay of peak-to-peak amplitude differences, (7) Bottom-left: Strip plot with box plot overlay showing signal energy distribution by class, (8) Bottom-center: Histogram with KDE overlay of signal baseline drift (difference between first and last 10 values), (9) Bottom-right: Population pyramid comparing the distribution of signal complexity measures between normal and abnormal ECG readings. Use different colors for normal (0) and abnormal (1) cases throughout all subplots.

Files

CSV ecg.csv

Reference Image

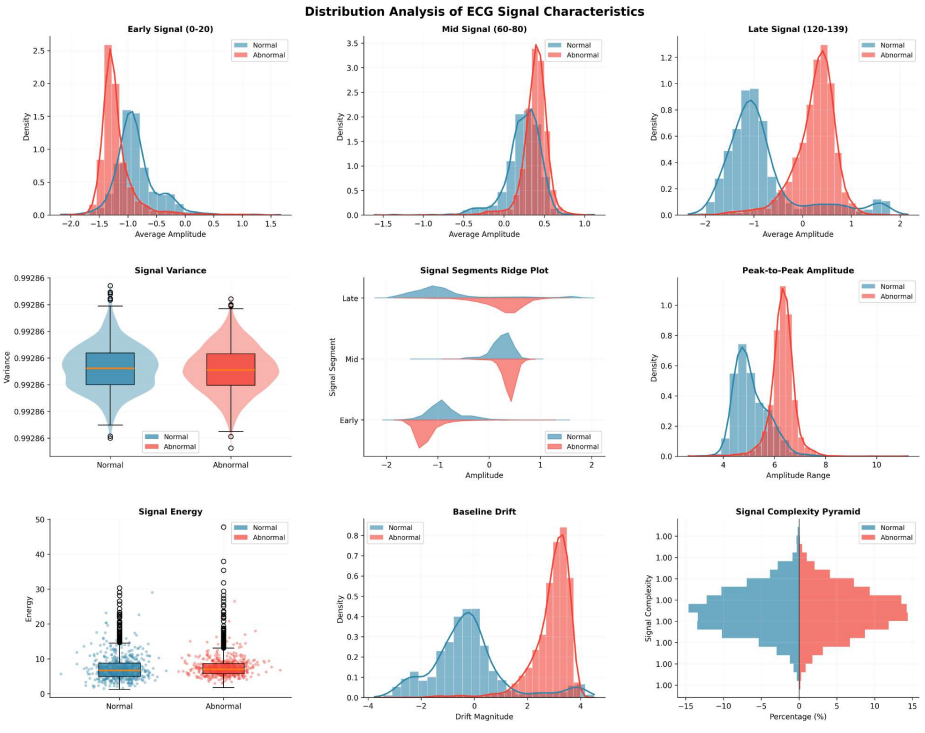


Figure 6: An example of a complex distribution visualization task from the PlotCraft benchmark. The model is required to generate a 3x3 grid of plots to compare ECG signal distributions, showcasing the benchmark's focus on sophisticated, multi-panel figures.

Deviation The Deviation category includes tasks that visualize the difference or variance of data points against a fixed baseline or between different groups. An example is shown in Figure 12, where the task is to analyze prediction errors: "Create a 3x3 grid of composite visualizations analyzing the deviation patterns in Titanic passenger survival predictions."

TO DO

Example 2 - Correlation

Instruction

Create a comprehensive 3x3 subplot grid analyzing the relationship between economic indicators and Olympic performance across different regions. Each subplot should be a composite visualization combining multiple chart types:

Top row: (1) Scatter plot with regression line showing GDP vs Total Medals, overlaid with bubble sizes representing population and color-coded by region, plus marginal histograms; (2) Correlation heatmap of all numerical variables (gold, silver, bronze, total, gdp, population) with annotated correlation coefficients; (3) Scatter plot matrix (pair plot) of GDP, Total Medals, and Population with different colors for each region.

Middle row: (4) Box plots showing Total Medals distribution by region overlaid with individual data points as a strip plot; (5) Violin plots of GDP distribution by region combined with box plots inside; (6) Scatter plot of GDP vs Gold medals with best-fit lines for each region separately, including confidence intervals.

Bottom row: (7) Bubble chart showing Silver vs Bronze medals where bubble size represents GDP and colors represent regions, with trend lines; (8) Hexbin plot (2D histogram) of GDP vs Total Medals overlaid with scatter points colored by region; (9) Parallel coordinates plot showing standardized values of GDP, Population, Gold, Silver, Bronze, and Total medals with lines colored by region.

Files

olympics.csv

Reference Image

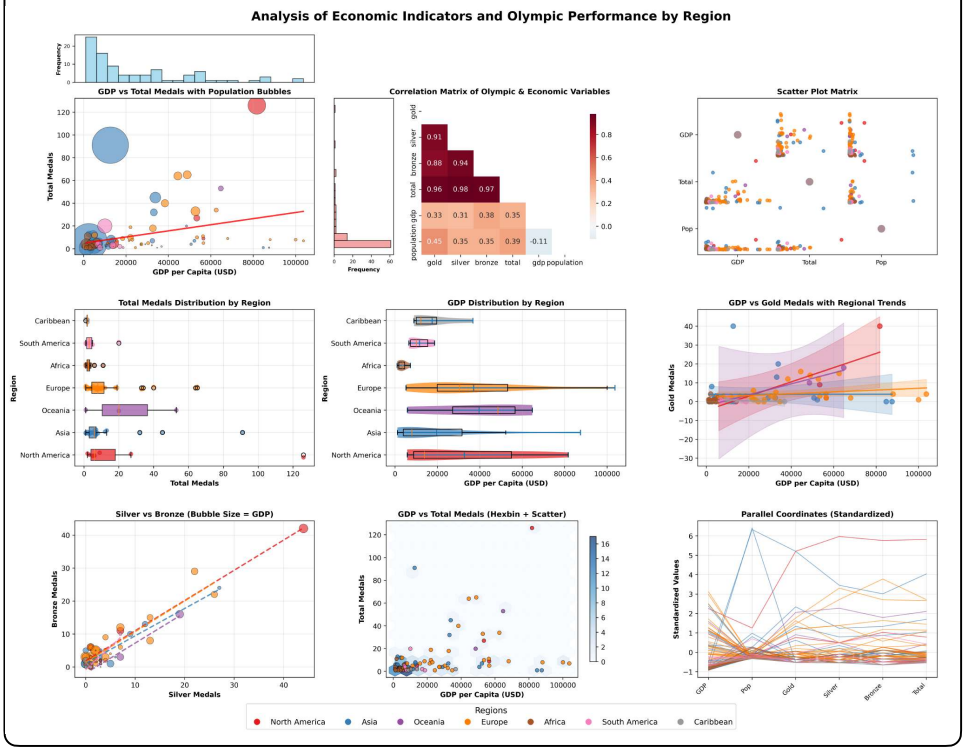


Figure 7: An example of a complex correlation task from the PlotCraft benchmark. The prompt requires a 3x3 subplot grid to visualize the relationship between economic indicators and Olympic performance, testing the model's ability to generate detailed, multi-faceted comparative analyses.

A.2 Thematic Coverage

The benchmark's thematic coverage is structured around eight high-level domains: **Finance** (Business & Finance), **Industry** (Industry & E-commerce), **Health** (Health & Medicine), **Research** (Sci-

TODO

Example 3 - Groups

Instruction

Create a comprehensive 3x3 subplot grid analyzing the clustering patterns and hierarchical relationships within the Brawl Stars competitive ecosystem. Each subplot must be a composite visualization combining multiple chart types:

Row 1: Player Performance Clustering Analysis
- Subplot 1: Scatter plot with KDE contours showing the relationship between total trophies and highest trophies, with points colored by experience level and sized by 3vs3 victories
- Subplot 2: Violin plot overlaid with box plots comparing trophy distributions across different player name color categories, with individual data points as a swarm plot
- Subplot 3: Parallel coordinates plot showing the relationships between trophies, experience level, solo victories, duo victories, and 3vs3 victories for top players

Row 2: Club Ecosystem and Member Dynamics
- Subplot 4: Network-style scatter plot showing club trophies vs member count, with bubble sizes representing required trophies and colors indicating club type, overlaid with trend lines for each club type
- Subplot 5: Stacked bar chart showing club member role distributions (President, Vice President, Senior, Member) combined with a line plot overlay showing average member trophies per club
- Subplot 6: Hierarchical cluster heatmap showing the correlation matrix between club characteristics (trophies, member count, required trophies) and member performance metrics

Row 3: Brawler Performance Segmentation
- Subplot 7: Grouped violin plots comparing trophy distributions for different brawler power levels (9, 10, 11), overlaid with median lines and quartile markers
- Subplot 8: Multi-dimensional scatter plot matrix showing relationships between brawler rank, trophies, and highest trophies for selected high-performing brawlers, with regression lines
- Subplot 9: Dendrogram-style cluster analysis combined with a heatmap showing player performance patterns across different brawler categories (tank, support, damage dealer, etc.)

Each subplot should reveal distinct clustering patterns, hierarchical relationships, or natural groupings within the competitive Brawl Stars community structure.

Files

CSV global_club_info.csv
CSV global_player_rankings.csv
CSV global_player_info.csv
CSV global_club_rankings.csv

Reference Image

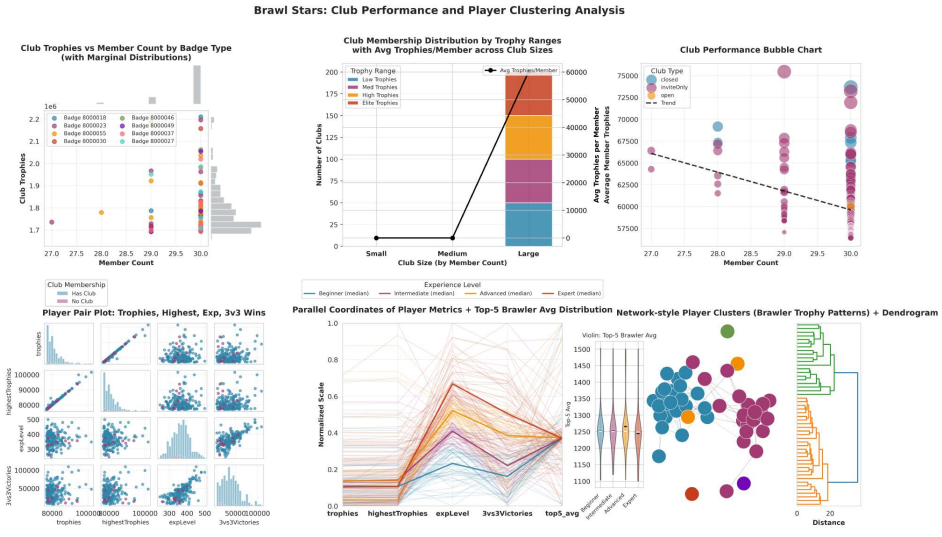


Figure 8: An example of a complex Groups visualization task. The model must generate a 3x3 grid to display clustering and hierarchical structures, testing its ability to render complex relational plots like dendrograms or network graphs.

TO DO

Example 4 - Change

Instruction

Create a comprehensive 3x2 subplot grid analyzing the temporal evolution of NIRF rankings across different educational categories from 2016-2021. Each subplot should be a composite visualization combining multiple chart types:

1. Top-left: Engineering rankings - Create a multi-line time series plot showing the score trajectories of the top 5 consistently ranked engineering institutes over years, overlaid with a filled area chart showing the score range (min-max) across all ranked institutes for each year.

2. Top-right: Management rankings - Develop a slope chart connecting 2016 and 2021 scores for the top 10 management institutes, with scatter points sized by their respective TLR (Teaching, Learning & Resources) scores and colored by their final 2021 ranking position.

3. Middle-left: Medical vs Dental comparison - Construct a dual-axis time series where the primary axis shows the average scores of top 10 medical institutes as a line chart with confidence bands, and the secondary axis displays the count of dental institutes participating each year as a bar chart.

4. Middle-right: University category analysis - Build a stacked area chart showing the cumulative distribution of universities across different score ranges (0-40, 40-60, 60-80, 80-100) over the years, with trend lines indicating the movement of median scores.

5. Bottom-left: Research institute performance - Create a combination of box plots showing score distributions for each year connected by violin plots, overlaid with individual trajectory lines for institutes that appeared in all available years.

6. Bottom-right: Overall ranking stability - Design a heatmap-style visualization showing rank changes over time for the top 20 overall ranked institutes, with additional line plots showing the coefficient of variation in scores across different ranking parameters (TLR, RPC, GO, OI, Perception) over the years.

Files

EngineeringRanking.csv
ManagementRanking.csv
MedicalRanking.csv
DentalRanking.csv
UniversityRanking.csv
ResearchRanking.csv
OverallRanking.csv

Reference Image

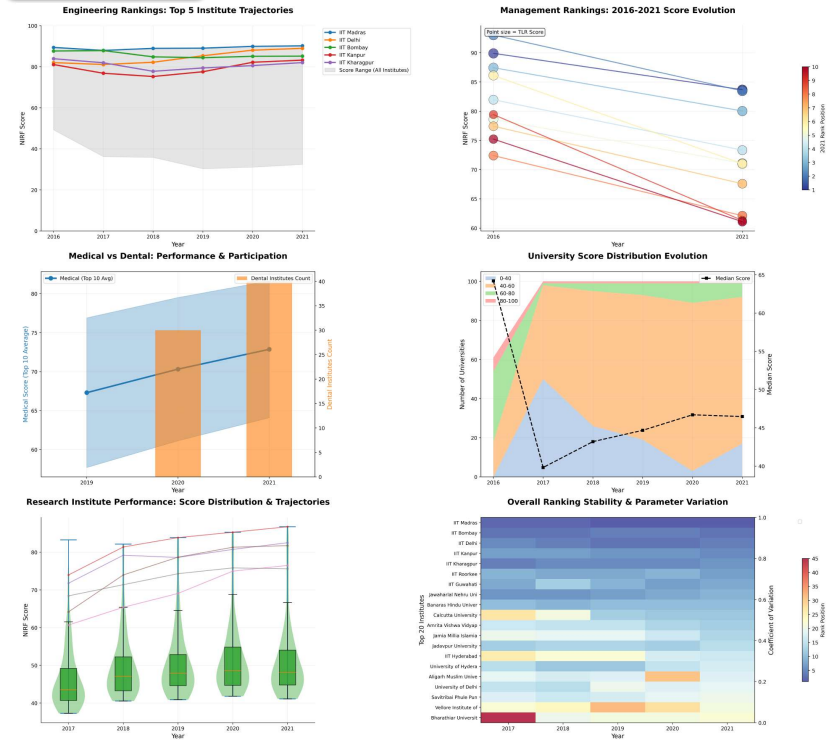


Figure 9: An example of a Change visualization task from the benchmark. This prompt requires a 3x2 subplot grid to track the temporal evolution of rankings, evaluating the model's ability to create detailed time-series visualizations.

TODO

Example 5 - Composition

Instruction

Create a composite visualization showing Netflix content composition across different dimensions. Design a 2x2 subplot grid where: (1) Top-left: A stacked bar chart showing the distribution of maturity ratings within each main genre, (2) Top-right: A pie chart displaying the overall composition of content by main genre, (3) Bottom-left: A horizontal bar chart ranking genres by their average release year to show content recency, and (4) Bottom-right: A treemap visualization showing the hierarchical composition of content by main genre and maturity rating combinations. Use consistent color schemes across all subplots and ensure proper titles and labels for each visualization.

Files

CSV Netflix Data new.csv

Reference Image

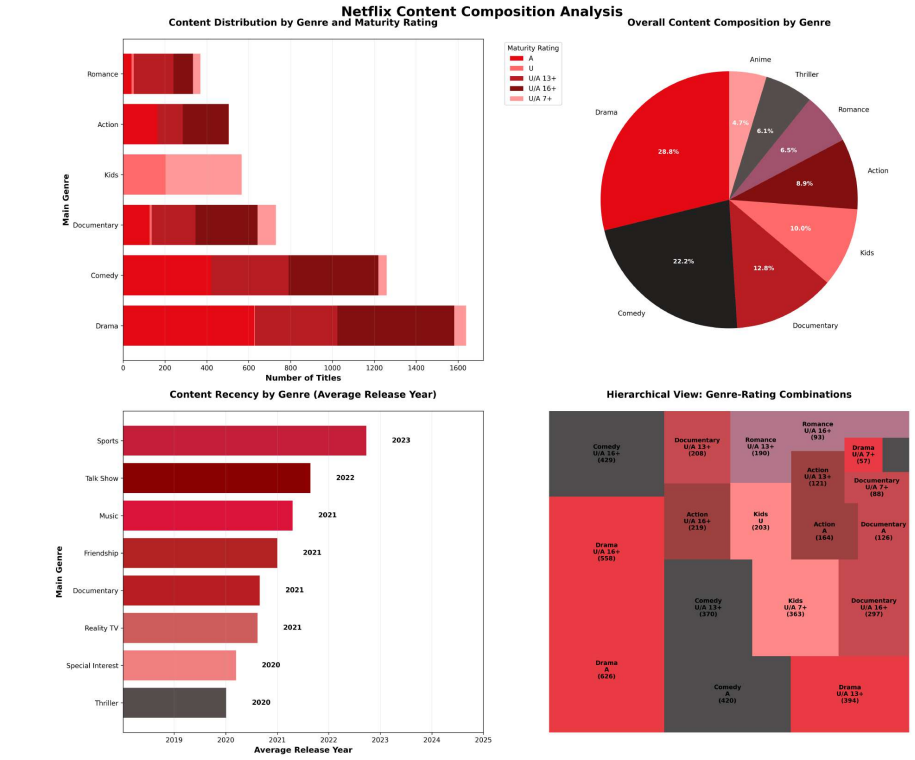


Figure 10: A Composition task example requiring the model to break down a dataset into its constituent parts. The instruction to use a 2x2 grid tests the ability to create comparative part-to-whole visualizations across different categories.

TO DO

Example 6 - Ranking

Instruction

Create a comprehensive ranking visualization that compares Udemy course performance across different metrics. Design a 2x2 subplot grid where each subplot combines multiple visualization elements:

1. Top-left: Create a horizontal bar chart showing the top 15 courses by number of subscribers, with bars colored by rating (use a color gradient from red for lower ratings to green for higher ratings). Overlay scatter points at the end of each bar to show the number of reviews.

2. Top-right: Build a lollipop chart displaying the top 12 courses by rating, where the stem length represents the rating value and the circle size represents the number of subscribers. Color-code the circles by instructional level.

3. Bottom-left: Design a stacked horizontal bar chart showing the top 10 instructors by total subscribers across all their courses. Each bar should be segmented to show the contribution of individual courses, with different colors for each course.

4. Bottom-right: Create a slope chart comparing the top 8 courses, showing the relationship between their ranking by subscribers (left side) versus their ranking by number of reviews (right side). Connect corresponding courses with lines, using different line styles or colors to highlight courses that maintain similar rankings versus those that change significantly.

Include appropriate titles, labels, and legends for each subplot. Use consistent color schemes and ensure all text is readable.

Files

CSV udemy_courses.csv

Reference Image

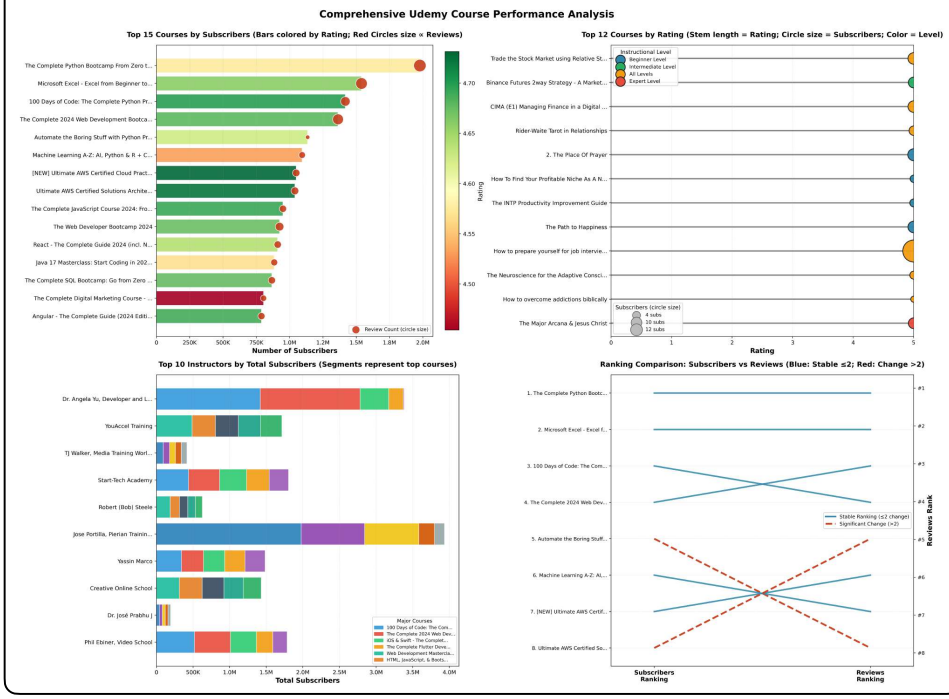


Figure 11: An example of a Ranking visualization task. The model is required to generate a 2x2 grid to compare and rank items across multiple metrics, assessing its ability to create clear and effective comparative bar charts or ordered plots.

TO DO

Example 7 - Deviation

Instruction

Create a 3x3 grid of composite visualizations analyzing the deviation patterns in Titanic passenger survival predictions. Each subplot should combine multiple chart types to show different aspects of deviation from expected survival patterns. Top row: (1) Diverging bar chart with error bars showing PassengerId ranges vs survival rate deviations from 50% baseline, overlaid with a line plot of cumulative deviation trends, (2) Dumbbell plot comparing actual vs expected survival rates across passenger ID quartiles with scatter points showing individual passenger deviations, (3) Area chart showing deviation magnitude distribution with overlaid violin plot of deviation densities. Middle row: (4) Radar chart displaying deviation metrics across multiple dimensions (early vs late passengers, ID clustering patterns) with overlaid polar scatter plot, (5) Slope chart connecting baseline expectations to actual outcomes across passenger segments with error band visualization, (6) Stacked area chart showing cumulative positive/negative deviations with overlaid trend line and confidence intervals. Bottom row: (7) Diverging lollipop chart of passenger ID bins vs deviation scores with histogram overlay, (8) Combined errorbar and stripplot showing deviation spread patterns across passenger groups, (9) Multi-layered deviation heatmap with contour lines and marginal distribution plots showing the relationship between PassengerId position and survival prediction accuracy.

Files

CSV All 1.csv

Reference Image

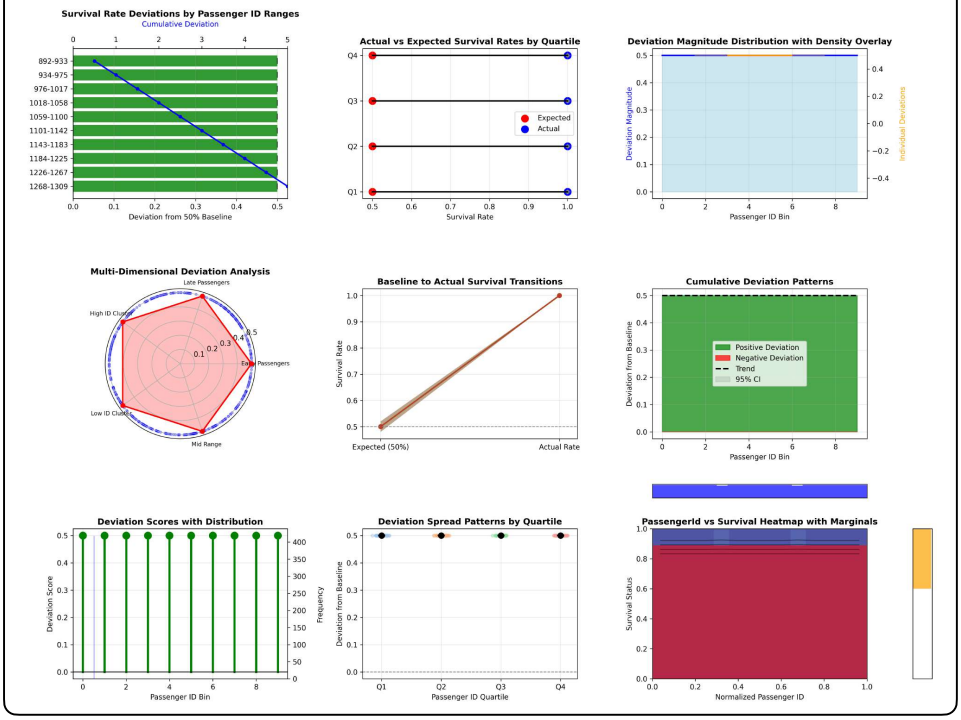


Figure 12: A Deviation task from the benchmark, requiring the analysis of prediction errors. The instruction to create a 3x3 grid tests the model's ability to visualize variance and differences, such as in divergence bars or error plots.

ence & Research), **Society** (Government & Society), **Media** (Culture & Media), **Tech.** (Technology & Computing), and **Env.** (Environment & Geospatial). These domains are further subdivided into 31 fine-grained sub-topics. A comprehensive list of all included sub-topics is presented in Table 6.

Table 6: This table illustrates the coverage of 31 fine-grained thematic topics within the PlotCraft dataset.

Type	Count	Type	Count	Type	Count	Type	Count
Manufacturing, Logistics	18	Supply Chain, Retail	17	Sales, Customer Behavior	22	Energy	11
Medical Imaging	25	Clinical Trials	16	Public Health	20	Genomics for Medicine	11
Digital Health Records	19	Physics & Astronomy	14	Biology (non-medical)	15	Chemistry	13
Material Science	12	Social Sciences Research	15	Civics & Elections	10	Demographics	12
Urban Planning	14	Transportation	16	Education	18	Arts & Literature	11
Movies & TV	13	Music, Sports	12	News & Journalism	19	Computer Science & AI	44
Software & Code	28	Internet & Social Media	21	Cybersecurity	14	Climate & Weather	12
Satellite Imagery	7	Ecology & Agriculture	12	Geographic Information	–	–	–

A.3 Task Complexity

Tasks within the PlotCraft benchmark are stratified into three distinct levels of complexity:

- **Easy**: Tasks require the generation of a single, standard chart (e.g., one bar chart, one line chart, or one scatter plot) to visualize the data.
- **Medium**: Tasks involve creating a composite visualization. This can be either: (a) a single figure that integrates multiple plot types or variables (e.g., a bar chart with a line plot overlay), or (b) a multi-panel grid (e.g., 2x1, 2x2) composed of simple, individual plots.
- **Hard**: Tasks demand the creation of a complex, multi-panel grid (e.g., 2x2, 3x3) wherein each individual subplot is itself a composite chart. For example, a 2x2 grid where each of the four plots contains both a histogram and a Kernel Density Estimation (KDE) curve.

To illustrate these levels, Figure 13 displays the instructions and raw data for three tasks of varying difficulty, all derived from the `firethorn-10-world-co2-emission-analysis` dataset. Figure 14 then shows the corresponding ground-truth reference images for each of these three instructions.

A.4 Sandboxed Envirnment

To ensure the safe, consistent, and reproducible execution of all model-generated code, we constructed a dedicated sandboxed environment containerized using Docker. This approach provides an isolated and standardized platform, guaranteeing that all models are evaluated under identical conditions.

The environment is based on Python 3.13 and comes pre-installed with a comprehensive suite of libraries essential for data analysis and visualization. The foundational libraries include Pandas for data manipulation and NumPy for numerical operations. For visualization, the environment is equipped with Matplotlib as the primary plotting library, complemented by a wide array of higher-level and specialized libraries to support diverse charting requirements. These include:

- **Seaborn**: For high-level statistical graphics.
- **Plotly**: For interactive charts.
- **Squarify**: For creating treemaps.
- **scikit-learn**: For generating machine learning-related plots like confusion matrices.
- **statsmodels**: For advanced statistical visualizations.

All evaluations are conducted on a server equipped with 128 CPU cores and 1024 GB of RAM. Each code execution is performed within its container without network access and is subject to a strict execution timeout of 120 seconds to prevent runaway processes. This fully-specified, sandboxed setup eliminates variability from system configurations and provides a fair and secure assessment of each model's code generation capabilities.

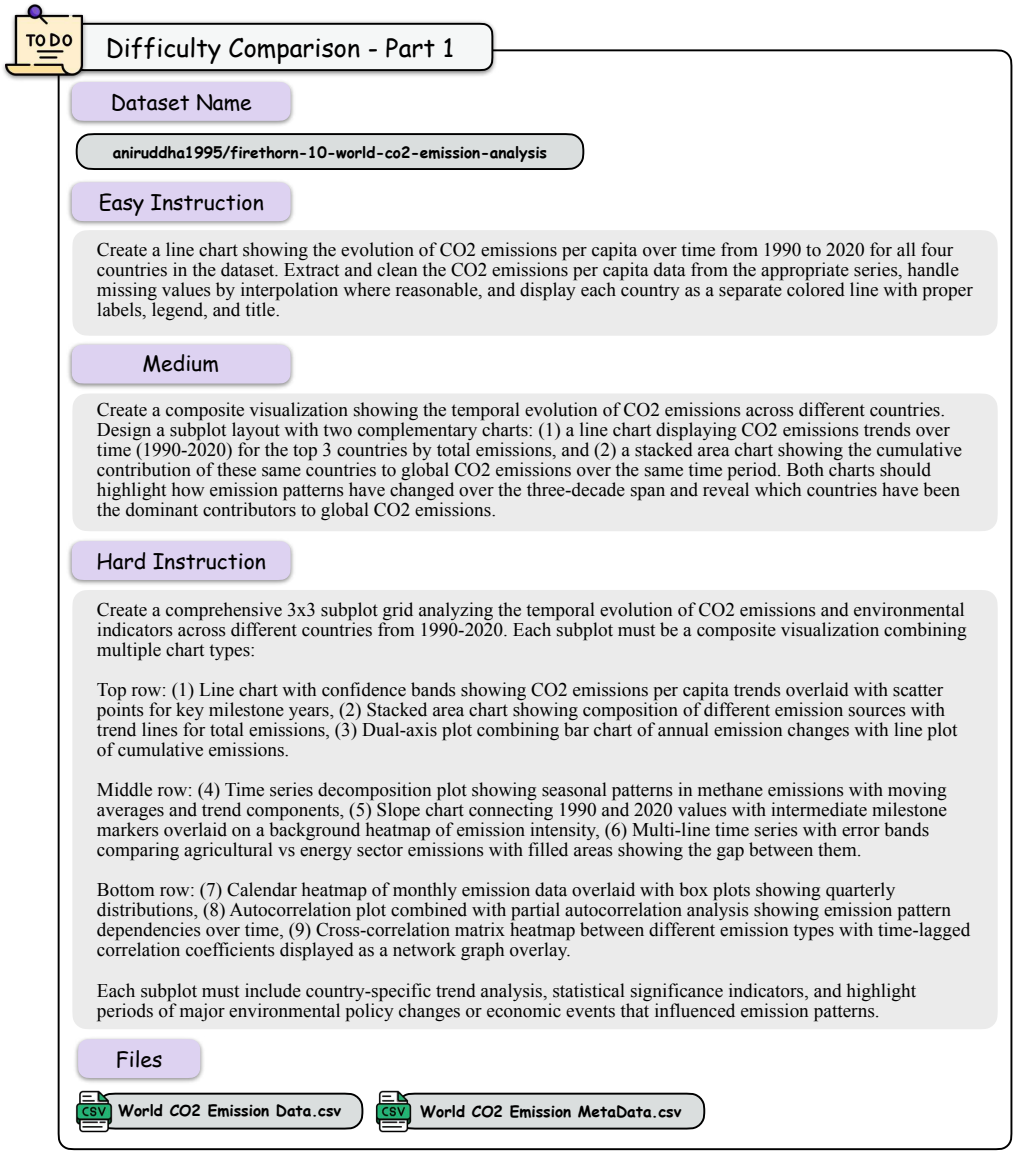


Figure 13: Example tasks of varying complexity levels from the PlotCraft benchmark. For a single dataset (`firethorn-10-world-co2-emission-analysis`), this figure shows the raw data and the natural language instructions for an Easy, Medium, and Hard task.

B Benchmark Data Curation Details

B.1 Design Principles

The PlotCraft benchmark was designed to address critical gaps in existing evaluation methodologies, guided by four core principles for a more realistic and comprehensive assessment of LLM visualization capabilities.

- **Grounded in Real Data**: To ensure practical relevance and ecological validity, all tasks are constructed using authentic, real-world datasets. This principle allows the benchmark to circumvent the limitations and potential artifacts of synthetic data, which often lacks the noise, complexity, and inherent quirks found in genuine data sources. By grounding tasks in reality, PlotCraft provides a more robust evaluation of a model's ability to handle practical data visualization scenarios.

- **Built from Scratch**: To mitigate data contamination and prevent benchmark leakage, all tasks and corresponding code in PlotCraft are built from scratch. We utilize open-source datasets from Kaggle to generate novel visualization challenges, ensuring no overlap with existing benchmarks or code repositories. This approach guarantees a more accurate assessment of a model's true generalization capabilities.
- **Zero-Reference Generation**: All tasks are initiated from text-only instructions, with no reference images or code provided. This setup compels the model to generate a visualization from an abstract concept, mirroring the creative and interpretive workflow of a data analyst, rather than the simpler task of replicating a known visual pattern.
- **Compositional Complexity**: PlotCraft's tasks feature a wide spectrum of complexity, requiring the generation of multi-panel plots with intricate layouts (e.g., 2×2, 3×3 grids), shared axes, complex legends, and the combination of multiple chart types within a single figure. This focus on composition directly probes the spatial and logical reasoning skills that are undertested by current benchmarks.

B.2 Data Filtering

Our data curation process began with sourcing datasets from Kaggle. This process was structured into two distinct phases to ensure the final benchmark was of high quality, diverse, and robust.

The first phase consisted of a large-scale, automated pre-screening of an initial pool of 7,162 candidate datasets, which collectively comprised over 95,000 files and 25.6 billion data rows. To filter for quality and relevance, we applied quantitative thresholds for community engagement metrics (vote counts ¿ 20 and download frequency $\geq$ 100) and official Kaggle usability ratings. Datasets that did not meet these minimum criteria for community validation and documentation quality were programmatically excluded.

In the second phase, the resulting pool of high-quality datasets underwent a rigorous manual curation to select the final 140 core datasets for the benchmark. This selection was guided by three key principles. First, to ensure thematic diversity, we employed a stratified approach based on domain tags, guaranteeing broad coverage across topics like finance, healthcare, and technology. Second, we deliberately selected for a wide distribution of data volume and complexity, ensuring the inclusion of everything from small, clean tables to large, multi-file relational datasets. Finally, to mitigate data leakage, we conducted a thorough review to exclude datasets known to be prevalent in major pre-training corpora or other common visualization benchmarks.

The final curated collection for PlotCraft consists of 1,874 raw data files, totaling approximately 462 million data rows, providing a robust and novel foundation for evaluating visualization models.

B.3 Task and Instruction Writing

The creation of our benchmark's 491 unique visualization tasks was a meticulous, two-phase process designed to ensure depth, diversity, and a rigorous test of model capabilities.

The first phase, Comprehensive Task Generation, was conducted by a team of three data visualization experts. Adopting a systematic approach, the experts were tasked with authoring prompts for each of the 140 curated datasets. For each dataset, they targeted seven distinct, high-level visualization intents (Correlation, Deviation, Ranking, etc.) and aimed to create a variant for each of the three complexity levels (Easy, Medium, and Hard). To guide this process, the experts utilized a rich taxonomy of over 50 distinct chart types. This initial generation phase resulted in a large candidate pool of nearly 2,940 tasks (140 datasets × 7 intents × 3 complexity levels), providing comprehensive coverage of datasets, analytical goals, and difficulty.

The second phase, Collaborative Curation and Refinement, involved multiple rounds of review where the expert team discussed and filtered the large initial pool down to the final 491 tasks. Tasks were selected based on several criteria, including the clarity of the prompt, the feasibility of the visualization, and its analytical value. A key goal of this curation was to select the highest-quality examples while maintaining the balanced distribution across the three complexity levels established during generation. The final set reflects this, with 159 Easy, 163 Medium, and 169 Hard tasks.

Crucially, all final instructions were refined to be abstract and goal-oriented. They articulate the analytical requirements of the visualization, such as the desired layout, markings, and data transformations—without providing any guidance on code implementation. This approach compels the model to reason about the task from first principles, mirroring a more realistic human workflow.

The seven high-level visualization intents, along with the extensive range of chart types considered for each, are detailed below:

- **Correlation**: Scatter Plot, Bubble Plot, Scatter with Best Fit Line, Jitter Plot, Counts Plot, Scatter with Marginal Plots, Correlogram, Pairwise Plot, Network Graph, and Cluster Plot.
- **Deviation**: Diverging Bars Chart, Diverging Lollipop Chart, Slope Chart, Dumbbell Plot, Area Chart, Radar Chart, and Errorbar / Errorpoint Chart.
- **Ranking**: Ordered Bar Chart, Lollipop Chart, Dot Plot, Slope Chart, Dumbbell Plot, Stacked Bar Chart, and Diverging Lollipop Chart.
- **Distribution**: Histogram, Density Plot, Box Plot, Violin Plot, Joy Plot / Ridgeline Plot, Population Pyramid, Jitter Plot / Stripplot, and Categorical Plots.
- **Composition**: Stacked Bar Chart, Stacked Area Chart, Pie Chart, Treemap, and Waffle Chart.
- **Change**: Line Chart / Time Series Plot, Area Chart, Time Series with Error Bands, Calendar Heatmap, Seasonal Plot, Slope Chart, Dumbbell Plot, and Time Series Decomposition Plot.
- **Groups**: Dendrogram, Cluster Plot, Network Graph, Radar Chart, Treemap, Parallel Coordinates Plot, and Grouped Charts.

B.4 Multi-turn Coversation

The following figures 15, 16, 17, and 18 provide several examples of the setup for our multi-turn refinement tasks. Each example consists of two key components: (1) the rendered image produced by an initial, intentionally flawed code implementation, and (2) the corresponding human-authored natural language request for its modification.

B.5 Quality Control

To guarantee the robustness of PlotCraft, we implemented a multi-stage quality control protocol involving cross-validation and consensus-based adjudication.

Multi-turn Refinement Verification Ensuring the correctness of the multi-turn tasks required verifying the logical consistency between the faulty image, the error description, and the refinement instruction. We employed a **triple-verification strategy** for this phase:

1. **Triplet Validation**: Each generated triplet (Original Instruction, Faulty Image, Refinement Request) was reviewed by three independent annotators.
2. **Factuality & Consistency Check**: Annotators verified two specific conditions: First, *Error Existence*—confirming that the errors described in the refinement request (e.g., "the text overlaps") were visually present in the rendered image. Second, *Instruction Consistency*—ensuring the refinement request did not contradict the original visualization goal.
3. **Majority Vote & Consensus**: A task was only accepted if it received a unanimous "Pass" vote. In cases of partial agreement (2/3), the triplet underwent a consensus discussion phase to determine if the refinement prompt could be polished. Triplets failing to reach consensus were discarded.

This strict verification loop ensures that all multi-turn interactions in PlotCraft reflect grounded, logical, and realistic user behaviors.

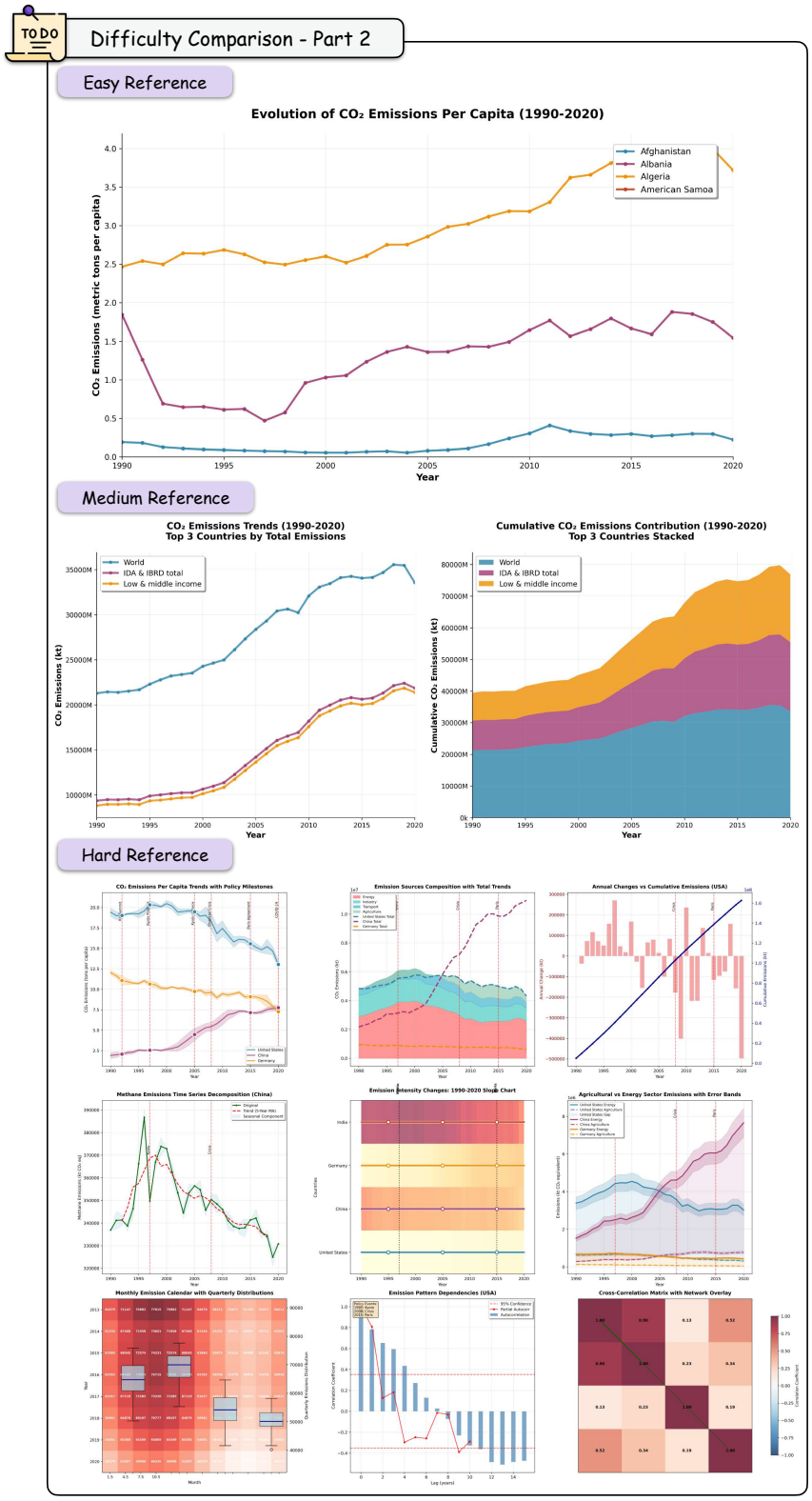
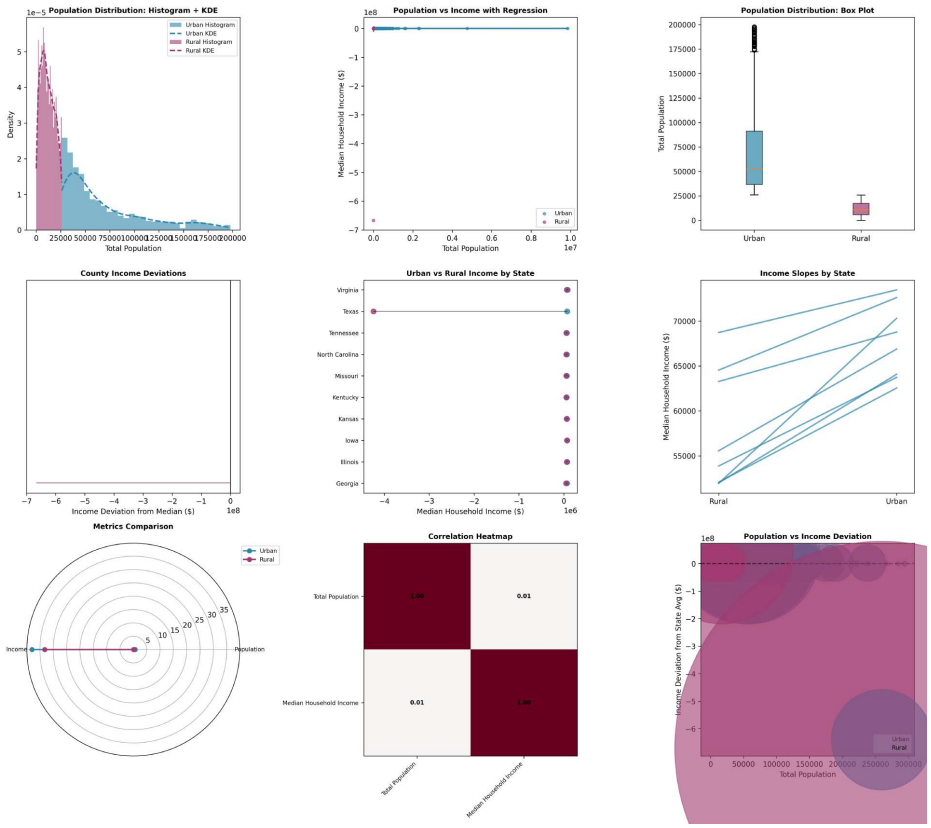


Figure 14: Reference images corresponding to the three task instructions shown in Figure 13. These images represent the ground-truth visualizations for the Easy, Medium, and Hard tasks, respectively, illustrating the expected output for each complexity level.

FAIL

Faulty Code - 1

Rendered Image



Modification Request

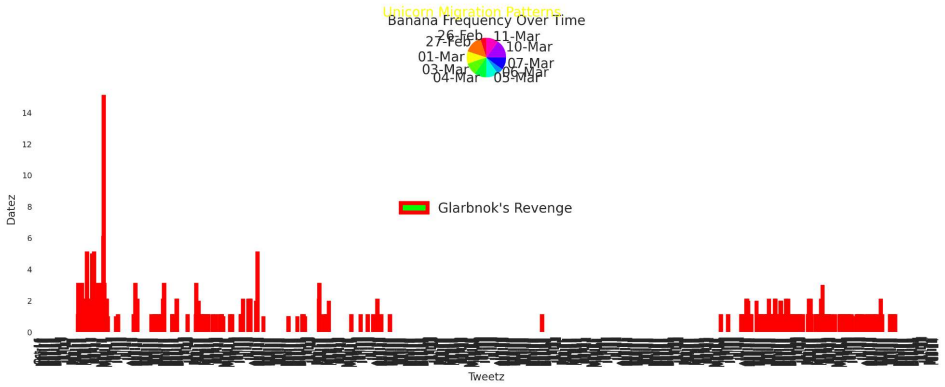
To improve this chart, the following specific actions are recommended:
1. Complete Missing Visualizations: The primary issue is incompleteness. Re-generate the following subplots to include all required components: Subplot (1, 0): Implement a proper histogram for tweet length, overlay the KDE curve, and add the requested box plot (e.g., below the main plot). Subplot (1, 1): Re-do the analysis to show the frequency of the top N hashtags over time, not the number of hashtags per tweet. Add trend lines for these top hashtags. Subplot (1, 2): Add the 'percentage change indicators' to the stacked bars. Subplot (2, 1): Add marginal distribution plots (histograms or bar plots) to the top and right of the heatmap to show tweet counts by hour and day of the week, respectively. Subplot (2, 2): Add the 'violin plot distributions' for different time periods alongside the line chart to show the spread of sentiment scores. 2. Resolve Text Overlap and Formatting: Subplots (0, 2) and (1, 2): Rotate the x-axis tick labels by 45 or 90 degrees to prevent overlap. Alternatively, reduce the number of ticks displayed by showing only one label per year. Subplot (1, 0): Format the y-axis tick labels to a reasonable precision (e.g., '0.004') instead of the long float. General: Establish a stronger typographic hierarchy. Increase the font size and weight of the main figure title (if one were added) and ensure subplot titles are clearly distinct from axis labels. 3. Enhance Visual Elements: Subplot (0, 0): The bars are nearly invisible. Increase their width and change their color to one with much higher contrast against the white background (e.g., a medium gray or blue). 4. Improve Layout and Spacing: Increase the vertical and horizontal spacing between subplots to prevent titles from crowding the plots above them and to create a more balanced, less cramped appearance. Using a function like `plt.tight_layout(pad=3.0)` or `fig.set_constrained_layout(True)` would help.

Figure 15: A multi-turn task example with multiple errors. Subplot (1, 0) fails to implement the required histogram, KDE curve, and boxplot. Furthermore, subplot (2, 2) exhibits severe rendering artifacts, including element overlap and content extending beyond the subplot boundaries.

FAIL

Faulty Code - 2

Rendered Image



Modification Request

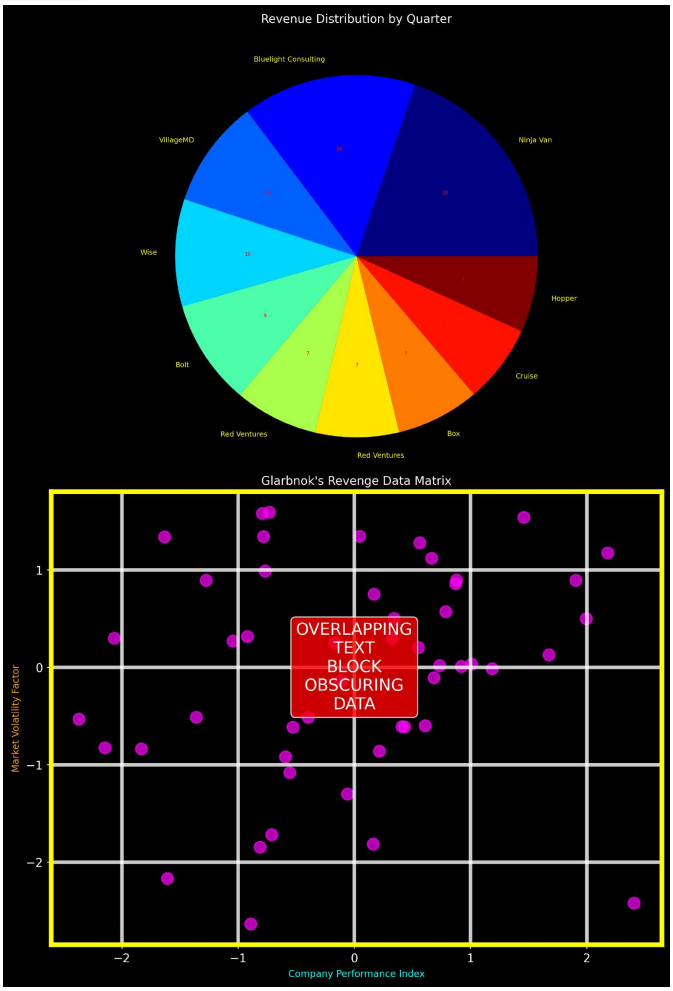
The generated chart is fundamentally flawed and cannot be salvaged. It must be recreated from scratch to meet the user's requirements. 1. Correct Chart Type: Replace the bar chart and pie chart with a single line chart as requested. 2. Correct Data and Labels: The chart must plot the frequency of Khaadi tweets over time. The x-axis should be labeled 'Date' and the y-axis should be labeled 'Number of Tweets' or 'Tweet Frequency'. 3. Add a Relevant Title: The title should be descriptive and relevant, for example, 'Daily Tweet Frequency for Khaadi'. 4. Ensure Text Readability: The x-axis date labels must be formatted and spaced properly to be legible. If there are too many dates, consider rotating the labels or plotting data at a weekly interval. 5. Professional Aesthetics: Remove all nonsensical elements (the pie chart, the incorrect legend). Use a simple, professional color palette, such as a single shade of blue for the line. Ensure the title is bold and larger than the axis labels to establish a clear visual hierarchy. The layout should be balanced, utilizing the available space effectively without excessive white space.

Figure 16: An example of incorrect chart type and poor aesthetics. The generated code produces pie charts, which violates the instruction, and utilizes a color palette with excessively high contrast, diminishing the visual quality.

FAIL

Faulty Code - 3

Rendered Image



Modification Request

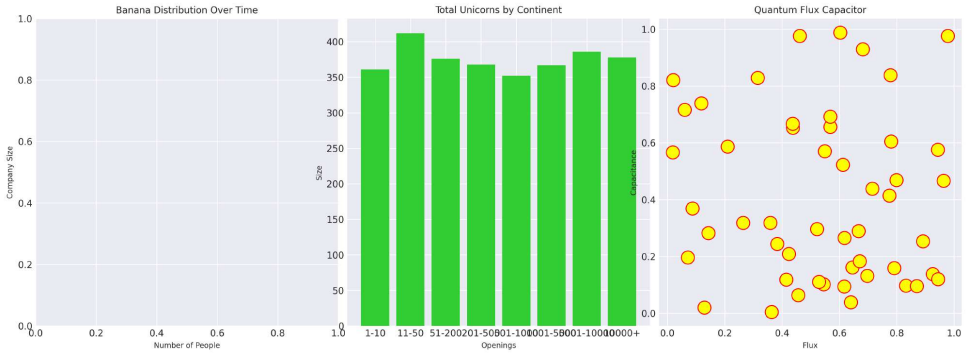
The generated chart is completely incorrect and does not address the user's task in any way. It must be discarded and created from scratch. 1. Chart Type and Layout: Replace the current pie chart and scatter plot with a single horizontal bar chart in a 1x1 layout. 2. Data and Ranking: The chart must visualize the top 10 tech startups ranked by the total number of job openings. The y-axis should list the company names, and the x-axis should represent the 'Total Job Openings'. The bars should be ordered descendingly, with the company having the most job openings at the top. 3. Annotations: Add data labels to the end of each bar to display the exact total job count for each company. This fulfills a specific requirement of the prompt. 4. Formatting and Professionalism: Background and Grid: Use a white background with light gray, subtle horizontal gridlines to guide the eye. Remove the heavy, colored border. Colors: Use a single, neutral color (e.g., a medium blue or gray) for all bars to maintain a professional look. Avoid rainbow or overly saturated color schemes. Typography: Set a clear title, such as 'Top 10 Tech Startups by Total Job Openings', in a larger, bold font. Use a standard, legible font for all axis labels, tick labels, and data annotations. Ensure the y-axis labels (company names) are fully readable and not truncated. Axes: Label the x-axis 'Total Job Openings' and the y-axis 'Company'.

Figure 17: An example of incorrect layout and suboptimal color choice. The code fails to adhere to the specified 1x1 grid layout, and the visualization suffers from an oversaturated color scheme that compromises professional appearance.

FAIL

Faulty Code - 4

Rendered Image



Modification Request

The generated chart is a complete failure and does not address the user's prompt in any way. It must be recreated from scratch. 1. Layout and Chart Type Correction: The entire visualization needs to be rebuilt using the specified 2x1 layout. The top subplot (0, 0) must be a stacked bar chart, and the bottom subplot (1, 0) must be a pie chart. 2. Content Correction for Subplot (0, 0): This plot should be a stacked bar chart showing the distribution of job categories across different company sizes. The x-axis should represent company size ranges (e.g., '1-10', '11-50'), and the y-axis should represent the number of jobs. Each bar should be segmented by job category (e.g., Engineering, Sales), and a legend should be provided to identify the categories. 3. Content Correction for Subplot (1, 0): This plot should be a pie chart illustrating the total proportion of job openings for each company size category. Each slice should be clearly labeled with the corresponding company size and its percentage of the total. 4. Text and Labels: All titles and axis labels must be corrected to be relevant to the task. For example, the title for the top plot could be 'Hiring Distribution by Job Category and Company Size', and for the bottom plot, 'Proportion of Job Openings by Company Size'. 5. Professional Formatting: Adopt a professional aesthetic. Use a white background with subtle, light gray gridlines. Choose a harmonious and distinct color palette for the stacked bars and pie slices. Ensure a clear visual hierarchy by making the main titles bold and slightly larger than the axis labels.

Figure 18: An example where chart types are correct but formatting is poor. The visualization suffers from overlapping x-axis tick labels, which impairs readability, and uses a default gray background that lacks professional polish.

C EVALUATION METRICS

This section details the comprehensive prompt in Figure C, C, C, C and scoring rubric used to evaluate the generated visualizations. Our evaluation is structured around two primary dimensions: **Task Compliance** and **Chart Quality**, each with a set of granular sub-metrics as defined below.

1. TASK COMPLIANCE (BINARY SCORING: 0/1)

For each criterion, a binary score is assigned: `1` for compliance (requirement met) or `0` for non-compliance (requirement not met).

1. **Layout Compliance:**
   - *Question:* Does the chart follow the required layout specification (e.g., 1x1, 2x2)?
   - *Score:* `1` if the layout matches the requirement exactly; `0` otherwise.
2. **Chart Type Compliance:**
   - *Question:* Does the chart use the correct specified chart type(s)?
   - *Score:* `1` if all chart types match the requirement; `0` otherwise.
3. **Visualization Requirement Fulfillment:**
   - *Question:* Does the chart fulfill the core visualization goal (e.g., showing a relationship, displaying a trend)?
   - *Score:* `1` if the core visualization requirement is met; `0` otherwise.
4. **Complete Task Fulfillment:**
   - *Question:* Are all specified requirements from the task instruction completed?
   - *Score:* `1` if all requirements are fulfilled; `0` if any requirement is missing.

2. CHART QUALITY (3-LEVEL SCORING: 0/1/2)

For each criterion, a score from 0 to 2 is assigned based on the following rubric.

1. **Clarity (No Overlap):**

   Score 2 No overlap exists between any elements; all components are clearly separated.
   Score 1 Minor overlap exists but does not significantly impact readability.
   Score 0 Significant overlap exists, severely affecting the chart's readability.
2. **Layout Quality:**

   Score 2 Excellent layout with well-proportioned elements and optimal spacing.
   Score 1 Good layout with acceptable element sizes and spacing, but with minor imperfections.
   Score 0 Poor layout with inappropriately sized, cramped, or poorly spaced elements.
3. **Color Quality:**

   Score 2 Excellent, harmonious color scheme with appropriate contrast and visual appeal.
   Score 1 Good color scheme with acceptable harmony and contrast, but with minor issues.
   Score 0 Poor color scheme with clashing, harsh, or overly dull colors.
4. **Text Readability:**

   Score 2 All text content is correct, appropriately sized, and clearly legible.
   Score 1 Text contains minor issues (e.g., small font size, minor typos) that do not significantly impair understanding.
   Score 0 Text has significant correctness or legibility issues (e.g., wrong labels, unreadable font).
5. **Professional Formatting:**

   Score 2 (Publication-Ready) The chart is highly professional and polished, adhering to formal publication standards (e.g., white background, subtle gridlines, clear typographic hierarchy).

Score 1 (Needs Revision) The chart is functional but lacks professional refinement. It may use a plain default style, have a weak visual hierarchy, or heavy borders.

Score 0 (Unacceptable) The chart uses a non-standard, themed style inappropriate for formal contexts (e.g., non-white background, high-contrast gridlines).

Prompt C.1: Evaluation Prompt - Part 1

```
**Role and Goal:**
You are a meticulous data visualization quality inspector. Your
    task is to evaluate a generated chart based on a user's task
     prompt and the chart's visual properties. The evaluation is
     divided into two main categories: Task Compliance and Chart
     Quality.

**Task Prompt Format:**
The user's request follows this format:
```
Task
Category: {task_category}
Instruction: {task_instruction}
```

**Evaluation Categories:**

## 1. Task Compliance (Binary Scoring: 0/1)
For each criterion, provide a binary score: `1` for compliance (
    requirement met) or `0` for non-compliance (requirement not
    met).

1. **Layout Compliance:**
   - **Question**: Does the chart follow the required layout
       specification (e.g., 1x1, 2x2, 2x3)?
   - **Score**: `1` if the layout matches the requirement
       exactly. `0` if the layout differs from what was
       specified.

2. **Chart Type Compliance:**
   - **Question**: Does the chart use the correct chart type as
       specified (e.g., bar chart, line chart, scatter plot)?
   - **Score**: `1` if the chart type matches the requirement.
       `0` if a different chart type was used.

3. **Visualization Requirement Fulfillment:**
   - **Question**: Does the chart fulfill the specific
       visualization requirement (e.g., showing relationship
       between two variables, displaying trends over time)?
   - **Score**: `1` if the core visualization requirement is met
       . `0` if the requirement is not addressed.

4. **Complete Task Fulfillment:**
   - **Question**: Are all specified requirements from the task
       instruction completed?
   - **Score**: `1` if all requirements are fulfilled. `0` if
       any requirement is missing or incomplete.
```

Prompt C.2: Evaluation Prompt - Part 2

```
## 2. Chart Quality (3-Level Scoring: 0/1/2)
For each criterion, provide a score from 0-2 with detailed
    explanations for each level.

1. **Clarity (No Overlap):**
   - **Score 2**: No overlap exists between any elements; all
       subplots, titles, axis labels, tick marks, legends, and
       text boxes are clearly separated.
   - **Score 1**: Minor overlap between text boxes or legends
       with plot content (data points, lines, bars) or border
       lines, but doesn't significantly impact readability.
   - **Score 0**: Significant overlap between subplots, titles,
       axis labels, tick marks, or other text elements that
       severely affects readability.

2. **Layout Quality:**
   - **Score 2**: Excellent layout with well-proportioned
       elements, optimal spacing, balanced white space
       distribution, and outstanding overall visual appeal.
   - **Score 1**: Good layout with reasonable element sizes and
       spacing, acceptable visual balance with minor
       imperfections.
   - **Score 0**: Poor layout with inappropriately sized
       elements, cramped or excessive spacing, unbalanced
       composition, or unappealing visual presentation.

3. **Color Quality:**
   - **Score 2**: Excellent color scheme with harmonious palette
       , appropriate contrast, visually appealing combinations,
       and effective use of distinct colors for differentiation.
   - **Score 1**: Good color scheme with acceptable harmony and
       contrast, minor issues that don't significantly impact
       aesthetics.
   - **Score 0**: Poor color scheme with clashing colors,
       excessive harsh contrasts, overly dull/muted colors, or
       ineffective use of similar colors that lack distinction.

4. **Text Clarity:**
   - **Score 2**: All text content is correct and appropriate,
       including accurate axis labels, proper titles, correct
       tick mark text, clear legends, and accurate text box
       content.
   - **Score 1**: Most text content is correct with minor issues
        that don't significantly impair understanding or convey
       wrong information.
   - **Score 0**: Text content has significant correctness
       issues including incorrect axis labels, inappropriate
       titles, wrong tick marks, unclear legends, or inaccurate
       text box content.
```

Prompt C.3: Evaluation Prompt - Part 3

```
5. **Formatting and Professional Standards:**
  - **Score 2**: (Excellent / Publication-Ready): The chart's
    formatting is highly professional, clean, and adheres
    strictly to formal publication standards. It appears
    polished and intentionally designed, not like a default
    software output. Key characteristics include:
    - A white background is used.
    - Gridlines, if present, are subtle (thin, light gray) and
      do not distract from the data.
    - A clear typographic hierarchy is established, with the
      main title being visually distinct (e.g., bolded and/or
      larger) from axis labels and other text.
    - All non-data elements (axes, ticks) are appropriately
      weighted and do not appear heavy or clumsy.
  - **Score 1**: (Good / Needs Revision): The chart is
    functional but lacks professional refinement and contains
    minor stylistic issues. It is clear but would require
    formatting adjustments before formal publication. Key
    characteristics include:
    - The background is white, but the overall aesthetic is
      plain or unpolished.
    - The title lacks emphasis (e.g., is not bolded), making the
      visual hierarchy weak.
    - It may have slightly heavy chart borders (spines) or
      default styling that feels more like a "first draft"
      than a final product.
  - **Score 0**: (Poor / Unacceptable for Formal Use): The chart
    uses a non-standard, themed style that is inappropriate
    for academic or professional contexts. It is immediately
    identifiable as a default output from an analysis tool.
    Key characteristics include:
    - It features a non-white background (e.g., gray, beige).
    - It employs high-contrast, distracting elements like white
      gridlines on a colored background.
    - The overall visual style is cluttered or stylized in a way
      that detracts from a formal, serious tone.
```

Prompt C.4: Evaluation Prompt - Part 4

```
**Output Format:**
Your response **MUST** be a single, valid JSON object, without
    any additional text before or after it. Use the exact
    structure below:

'''json
{
  "task_compliance": {
    "layout_compliance": {
      "score": <0_or_1>,
      "reason": "<State whether the layout matches requirements
         and specify deviations if score is 0.>"
    },
    "chart_type_compliance": {
      "score": <0_or_1>,
      "reason": "<State whether the chart type matches
         requirements and specify what was expected vs. actual
         if score is 0.>"
    },
    "visualization_requirement_fulfillment": {
      "score": <0_or_1>,
      "reason": "<State whether the core visualization
         requirement is met and specify what's missing if score
          is 0.>"
    },
    "complete_task_fulfillment": {
      "score": <0_or_1>,
      "reason": "<State whether all requirements are completed
         and list missing items if score is 0.>"
    }
  },
  "chart_quality": {
    "clarity_no_overlap": {
      "score": <0_1_or_2>,
      "reason": "<Describe the overlap situation and justify the
          score level.>"
    },
    "layout_quality": {
      "score": <0_1_or_2>,
      "reason": "<Evaluate element sizing, spacing, and overall
         visual balance.>"
    },
    "color_quality": {
      "score": <0_1_or_2>,
      "reason": "<Assess color harmony, contrast, and aesthetic
         appeal.>"
    },
    "text_clarity": {
      "score": <0_1_or_2>,
      "reason": "<Evaluate text readability, correctness, and
         positioning.>"
    },
    "formatting_and_professional_standards": {
      "score": <0_1_or_2>,
      "reason": "Evaluate formatting and professional standards
         .>"
    }
  }
}
'''
```

C.1 LLM JUDGE CASES

Case - 1 This case, presented in Figure 19, illustrates a complete evaluation performed by our Gemini-2.5-Pro judge, including the original instruction, the model-generated image, and the resulting scores. The example is notable because the generated visualization is of high aesthetic quality but exhibits significant Task Compliance failures. This highlights the importance of decoupling the evaluation of quality from correctness.

Specifically, several subplots do not adhere to the prompt's requirements:

- Subplot (1,0) is incorrectly implemented as a scatter plot instead of the required dumbbell plot.
- Subplot (1,1) is rendered as a line chart with error bands rather than the specified area chart.
- Subplots (0,0) and (0,1) fail to meet the "diverging" chart criteria, as they employ a monochromatic color scheme that does not differentiate between positive and negative values.

Case - 2 This case, presented in Figure 20, illustrates a generated visualization with a cascade of failures across multiple evaluation criteria, rendering it both incorrect and uninterpretable. The primary issues are categorized below.

- **Chart Type Non-Compliance:** The model fails to implement the specified chart types correctly. In subplot (1, 0), the bubbles are of uniform size and do not encode the transaction amount as required for a proper bubble chart. In subplot (2, 0), the treemap omits the required embedded bar charts, merely subdividing the areas instead.
- **Severe Element Overlap:** The visualization suffers from pervasive element occlusion that severely impacts readability. This includes illegible, overlapping x-axis tick labels in subplots (1, 0) and (2, 2); a legend in subplot (2, 1) that obstructs data points; and a dendrogram in subplot (2, 2) that clashes with its corresponding heatmap.
- **Inconsistent Color Scheme:** The use of color is critically flawed and misleading. In the first row, 'Fraud' is represented by red, but this is reversed in the parallel coordinates plot (1, 1), where 'Fraud' is incorrectly labeled as light blue. This semantic inconsistency makes the chart actively deceptive.
- **Poor Text Readability:** The chart has significant text-related issues. Multiple axis labels are illegible due to overlap, text within the treemap (2, 0) is too small to read, and some axes use raw, unformatted variable names (e.g., 'INIT_BALANCE'), which is unprofessional.

Case - 3 This case, presented in Figure 21, showcases a generated visualization that is highly successful in terms of both task compliance and overall chart quality. Its sole deficiency lies in the Professional Formatting sub-metric. The chart utilizes a non-standard, themed style that is inappropriate for formal publication; it features a gray background with high-contrast white gridlines, which is characteristic of a default software output (e.g., from Seaborn) rather than a polished, professional graphic. For publication-ready figures, a clean white background with subtle, non-distracting gridlines is the expected standard. This example underscores the importance of evaluating not just correctness, but also the fine-grained stylistic details that separate a functional plot from a professional one.

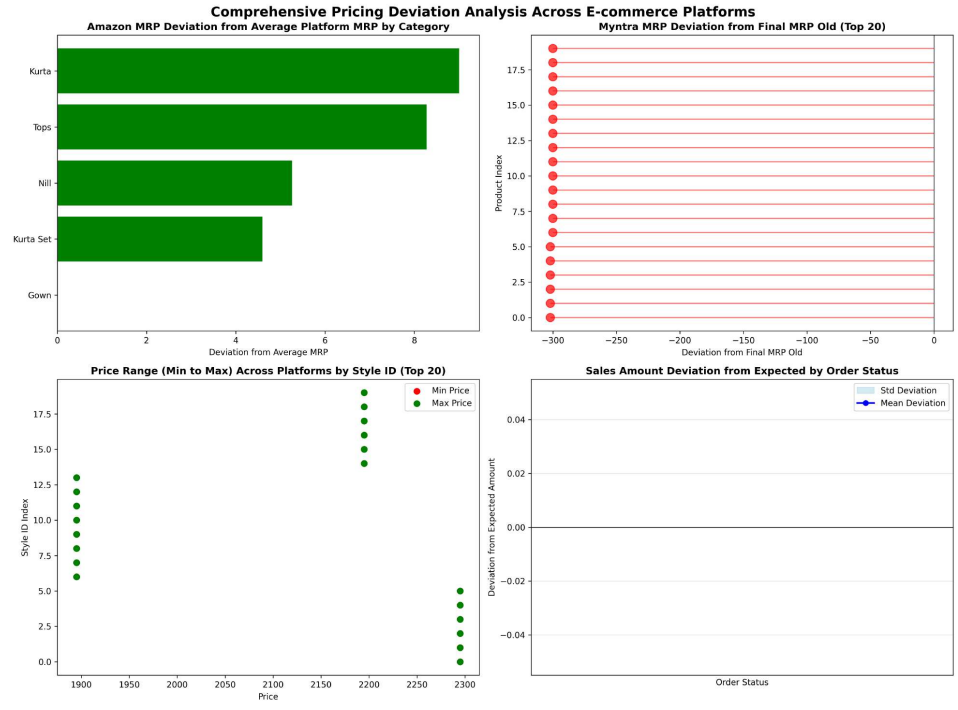
Case - 4 This case, presented in Figure 22, highlights how an otherwise high-quality visualization can be penalized for subtle but important flaws in its layout and clarity. While the chart successfully fulfills the core task requirements, its final score is reduced due to two specific issues. First, the layout is suboptimal, with excessive vertical white space between the main figure title and the subplot grid, creating a disjointed appearance. Second, the chart suffers from a minor clarity issue, as several x-axis tick labels exhibit slight overlap, which can impede readability. This example demonstrates the importance of meticulous polishing, a nuance that even capable models can overlook.

Judgement - 1

Instruction

Create a comprehensive pricing deviation analysis across multiple e-commerce platforms by combining data from three key files. Design a 2x2 subplot grid where each subplot shows the deviation of platform-specific MRPs from a baseline reference price. In the top-left, create a diverging bar chart showing how Amazon MRP deviates from the average MRP across all platforms for each product category. In the top-right, display a diverging lollipop chart comparing Myntra MRP deviations from the Final MRP Old baseline. In the bottom-left, construct a dumbbell plot showing the price range between the lowest platform MRP and highest platform MRP for each Style ID, highlighting the pricing spread. In the bottom-right, create an area chart with error bands showing the deviation of actual sale amounts from expected amounts (based on MRP) over different order statuses, using the Amazon sales data. Each subplot should use different colors to distinguish positive and negative deviations, and include reference lines at zero deviation.

Generation



Judgement

Layout Compliance	1	Clarity	2
Chart Type Compliance	0	Layout Quality	1
Requirement Fulfillment	0	Color Quality	2
Complete Task Fulfillment	0	Text Readability	2
		Professional Formatting	1

Figure 19: A complete evaluation case from our Gemini-2.5-Pro judge, displaying the original instruction, a generated image, and the final scores. This example highlights a common failure mode where a model produces a high-quality, aesthetically pleasing chart that nonetheless fails to comply with several key requirements of the prompt, particularly regarding the use of correct chart types.

Judgement - 2

Instruction

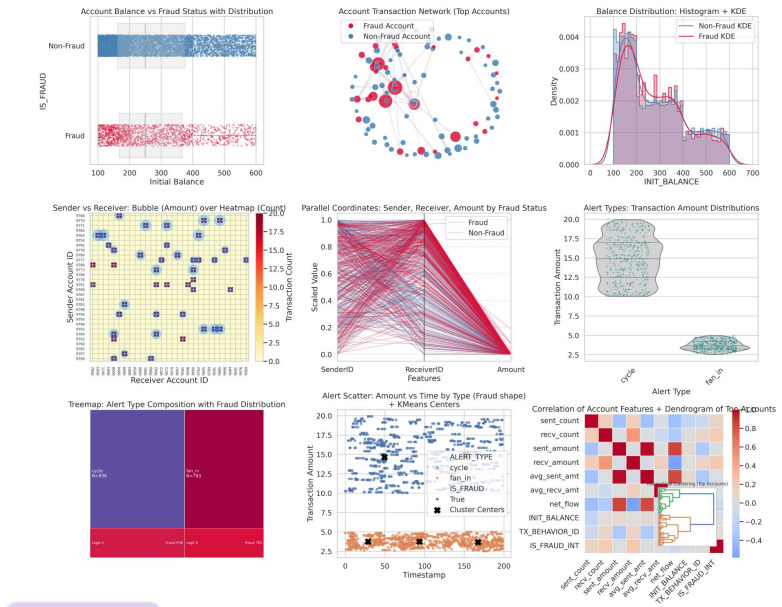
Create a comprehensive 3x3 subplot grid analyzing money laundering patterns and account clustering in the AML dataset. Each subplot should combine multiple visualization techniques:

Row 1: Account Analysis
- Subplot 1: Combine a scatter plot of account initial balance vs fraud status with overlaid box plots showing balance distribution by fraud category
- Subplot 2: Create a network graph showing account relationships through transactions, with nodes colored by fraud status and sized by transaction volume
- Subplot 3: Overlay a histogram and KDE curve showing the distribution of account balances, with separate curves for fraudulent and non-fraudulent accounts

Row 2: Transaction Flow Analysis
- Subplot 4: Combine a bubble chart (sender vs receiver accounts) where bubble size represents transaction amount, overlaid with a heatmap showing transaction density
- Subplot 5: Create a parallel coordinates plot showing the relationship between sender account, receiver account, transaction amount, and fraud status
- Subplot 6: Overlay violin plots and strip plots showing transaction amount distributions across different alert types

Row 3: Alert Pattern Investigation
- Subplot 7: Combine a treemap showing alert type composition with embedded bar charts showing fraud distribution within each alert type
- Subplot 8: Create a cluster analysis plot using transaction amounts and timestamps, with points colored by alert type and shaped by fraud status
- Subplot 9: Overlay a correlation heatmap of numerical variables with a dendrogram showing hierarchical clustering of accounts based on transaction patterns

Generation



Judgement

Layout Compliance	1	Clarity	0
Chart Type Compliance	0	Layout Quality	0
Requirement Fulfillment	1	Color Quality	1
Complete Task Fulfillment	0	Text Readability	1
		Professional Formatting	0

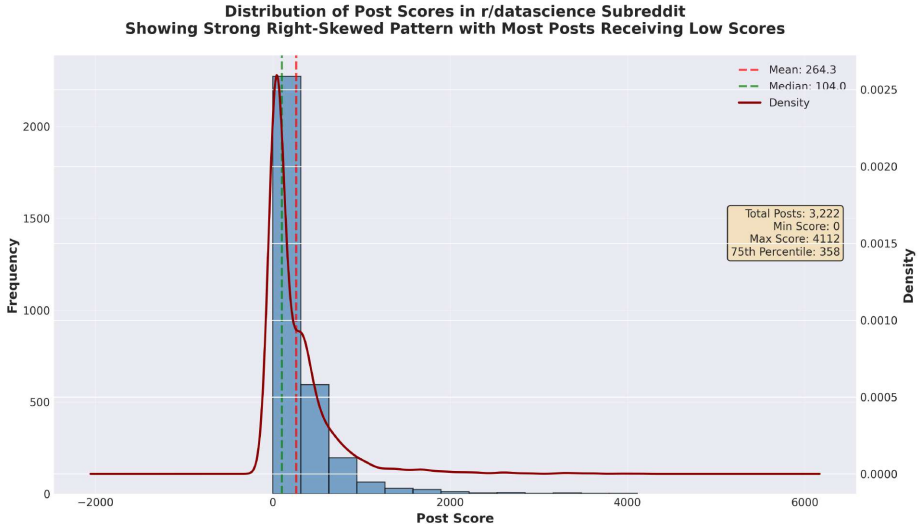
Figure 20: A case study of a generated visualization exhibiting a cascade of failures. The output suffers from non-compliance with chart type requirements, severe element overlap, a critically inconsistent and misleading color scheme, and poor text formatting, rendering it both incorrect and uninterpretable.

Judgement - 3

Instruction

Create a histogram showing the distribution of post scores in the Reddit r/datascience dataset. Use appropriate binning to reveal the underlying pattern of how posts are scored, and include proper axis labels and a title that describes what the visualization shows.

Generation



Judgement

Layout Compliance	1	Clarity	2
Chart Type Compliance	1	Layout Quality	2
Requirement Fulfillment	1	Color Quality	2
Complete Task Fulfillment	1	Text Readability	2
		Professional Formatting	0

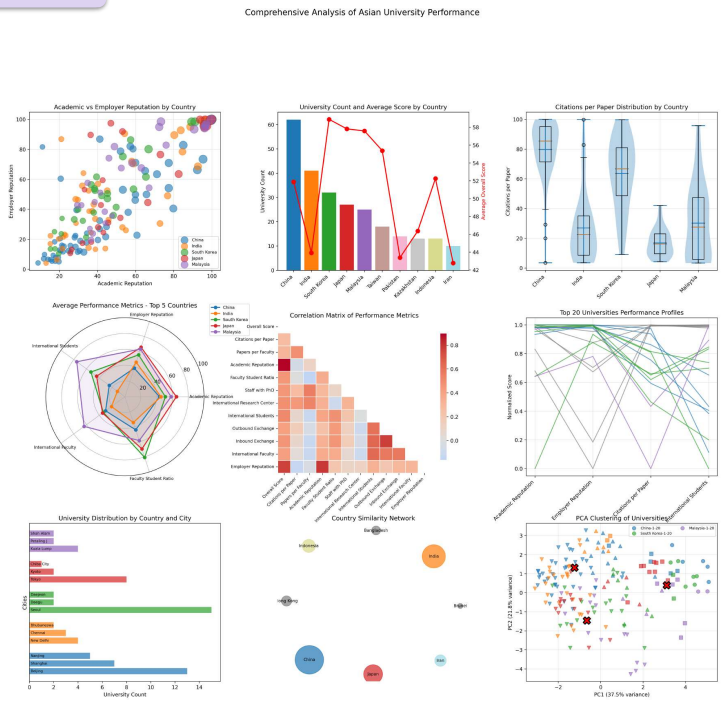
Figure 21: An example of a high-quality visualization that is penalized for a lack of professional formatting. While the chart correctly adheres to all task requirements, its use of a default gray background and high-contrast gridlines prevents it from meeting publication-ready standards.

Judgement - 4

Instruction

Create a comprehensive 3x3 subplot grid analyzing university performance clusters and regional patterns across Asian countries. Each subplot should be a composite visualization: (1) Top-left: Scatter plot with Academic Reputation vs Employer Reputation, overlaid with country-based color coding and bubble sizes representing Overall Score, plus marginal histograms showing distribution of each metric; (2) Top-center: Stacked bar chart showing count of universities by country, overlaid with a line plot showing average Overall Score per country; (3) Top-right: Box plot showing Citations per Paper distribution by country, overlaid with violin plots to show density distributions; (4) Middle-left: Radar chart comparing average performance metrics (Academic Reputation, Employer Reputation, International Students, International Faculty, Faculty Student Ratio) for top 5 countries by university count; (5) Middle-center: Heatmap showing correlation matrix of all numerical performance metrics, overlaid with hierarchical clustering dendrogram; (6) Middle-right: Parallel coordinates plot showing performance profiles of top 20 universities across key metrics (Academic Reputation, Employer Reputation, Citations per Paper, International Students), with lines colored by country; (7) Bottom-left: Treemap showing university count by country and city hierarchy, with cell sizes representing total universities and colors representing average Overall Score; (8) Bottom-center: Network graph showing country relationships based on similarity in performance metrics, with node sizes representing university count and edge weights representing similarity scores; (9) Bottom-right: Cluster scatter plot using PCA on all performance metrics, with points colored by country and shaped by ranking tiers (1-20, 21-50, 51-100), overlaid with cluster boundaries and centroids.

Generation



Judgement

Layout Compliance	1	Clarity	1
Chart Type Compliance	1	Layout Quality	1
Requirement Fulfillment	1	Color Quality	2
Complete Task Fulfillment	1	Text Readability	1
		Professional Formatting	1

Figure 22: An example of a high-quality visualization penalized for subtle layout and clarity issues. The excessive white space between the title and the plots, along with slightly overlapping x-axis labels, detracts from its overall professional quality.

Model	Single-Turn Generation			Multi-Turn Refinement			AVG score
	Pass Rate (%)	Task-Comp.	Quality	Pass Rate (%)	Task-Comp.	Quality	
Closed-source LLMs							
Claude-4.1-Opus (Anthropic, 2023)	76.20	1.93	4.20	81.44	2.05	5.22	6.70
Claude-4-Sonnet (Anthropic, 2023)	68.84	1.73	3.99	78.41	1.88	4.80	6.20
Gemini-2.5-Pro (Team, 2024)	41.34	1.15	2.31	58.86	1.51	3.80	4.39
ChatGPT-4o-Latest (OpenAI, 2023)	63.54	1.60	3.33	69.25	1.51	4.23	5.33
GPT-5 (OpenAI, 2025)	69.86	1.76	2.87	74.13	1.80	4.33	5.38
Grok-4 (xAI, 2025)	64.52	1.63	3.66	70.24	1.61	4.42	5.65
Open-source LLMs							
Kimi-K2 (Team et al., 2025b)	60.13	1.52	3.36	61.03	1.49	4.05	5.21
DeepSeek-V3.1 (DeepSeek-AI & etc., 2024)	55.71	1.49	3.20	56.86	1.50	3.99	5.09
DeepSeek-Coder-V2 (Guo et al., 2024)	47.45	1.23	2.68	68.23	1.47	4.12	4.76
DeepSeek-Coder-V2-Lite (Guo et al., 2024)	32.79	0.77	1.90	47.45	0.97	2.73	3.19
GLM-4.5 (Team et al., 2025a)	43.38	1.25	2.48	64.97	1.54	3.91	4.59
GPT-oss-120B (Agarwal et al., 2025)	48.23	1.32	2.68	29.69	0.77	1.87	3.32
GPT-oss-20B (Agarwal et al., 2025)	44.68	1.21	2.43	34.02	0.89	2.14	3.34
Seed-Coder-8B (Seed et al., 2025)	32.38	0.87	1.74	57.03	1.26	3.22	3.55
VisCoder-7B (Ni et al., 2025)	25.46	0.67	1.50	51.73	0.99	2.96	3.06
Qwen2.5-Coder-1.5B (Hui et al., 2024)	22.81	0.55	1.38	36.86	0.66	1.71	2.15
Qwen2.5-Coder-3B (Hui et al., 2024)	17.92	0.50	1.17	36.46	0.77	2.00	2.22
Qwen2.5-Coder-7B (Hui et al., 2024)	29.94	0.79	1.79	46.64	0.98	2.65	3.10
Qwen2.5-Coder-14B (Hui et al., 2024)	38.29	1.09	2.29	51.53	1.17	3.04	3.80
Qwen2.5-Coder-32B (Hui et al., 2024)	37.68	1.05	2.21	48.47	1.20	3.11	3.79
Qwen3-235B-A22B-2507 (Yang et al., 2025a)	56.01	1.53	3.31	71.69	1.70	4.49	5.51
Qwen3-Coder-480B-A35B (Hui et al., 2024)	61.30	1.56	3.21	75.97	1.75	4.46	5.49
Qwen3-Coder-30B-A3B (Hui et al., 2024)	52.55	1.32	2.85	73.12	1.55	4.18	4.95
PlotCraftor-30B-A3B (Ours)	64.36	1.73	4.09	77.11	1.76	4.74	6.16

Table 7: The complete quantitative results on PlotCraft for 24 LLMs across two settings: Single-Turn Generation and Multi-Turn Refinement.

D Additional Results

Table 7 presents the complete quantitative results for all 24 evaluated LLMs on the PlotCraft benchmark. The data reinforces the findings from our main analysis and further highlights the strong performance of our model.

Among all open-source models, PlotCraftor demonstrates a clear advantage, achieving an average score of 6.16. This result significantly surpasses other leading open-weight models, including the much larger Qwen3-235B (5.51) and Qwen3-Coder-480B (5.49). More importantly, PlotCraftor's performance closes the gap with top-tier proprietary systems, achieving a score nearly identical to that of Claude-4-Sonnet (6.20). These comprehensive results validate that PlotCraftor provides SOTA capabilities within the open-source community for complex data visualization tasks.

E SynthVis-30K Details

This section provides further implementation details for the multi-agent framework used to create the SynthVis-30K dataset.

Task Generation Agents and Criteria. The roles of both the Task Generator and the Task Judge were fulfilled by an ensemble of Large Language Models, primarily consisting of Claude-4-Sonnet and Qwen3-Coder-480B-A22B. The iterative refinement cycle for a given task was designed to be rigorous; a task was only finalized and accepted when the Task Judge agent could no longer identify any logical inconsistencies or feasibility issues with the proposed instructions.

Code Generation Agents and Termination Criteria. The Code Generator agent was also comprised of an ensemble of Claude-4-Sonnet and Qwen3-Coder-480B-A22B. The crucial role of the Visual Judge, responsible for assessing the quality of the rendered images, was performed by Gemini-2.5-Pro. The code generation process was constrained to a maximum of 10 refinement iterations. The cycle was considered successful and terminated early if the generated visualization achieved a perfect Task Compliance score (4 out of 4) and a Chart Quality score of at least 6 (out of 10), with the additional constraint that each of the five quality sub-metrics must score at least 1. If these criteria were not met within the 10-iteration limit, the entire task-code pair was discarded to maintain the high-quality standard of the final dataset.

SFT Trajectory Synthesis Details. The Chain-of-Thought (CoT) rationales for the single-turn training instances were generated using Claude-4-Sonnet. The final SynthVis-30K dataset is composed of 30,000 instances with a 2:1 split between single-turn and multi-turn trajectories, resulting in 20,000 single-turn generation instances and 10,000 multi-turn refinement instances.

F Evaluation Details

PlotCraft Evaluation. For the evaluation on our PlotCraft benchmark, all models were prompted using a standardized format. For the single-turn generation tasks, we used the prompt detailed in Prompt F. For the multi-turn refinement tasks, this same prompt served as the initial user turn in the conversation, followed by the specific refinement request.

VisEval and PandasPlotBench Evaluation. For our evaluation on the VisEval benchmark, we adopted the CoML table format and restricted our analysis to tasks specifically designed for the Matplotlib library. Similarly, for the PandasPlotBench benchmark, we exclusively evaluated the Matplotlib-based tasks. To ensure consistency with established practices for these benchmarks, the performance of the generated visualizations for both VisEval and PandasPlotBench was assessed using ChatGPT-4o-Latest as the automated judge.

Prompt F.1: Generation Prompt

````
You are an expert Python data visualization developer
    specializing in matplotlib and seaborn. Your task is to
    generate high-quality, executable Python code for data
    visualization based on the given task description and
    dataset information.
Output format:
- Provide only the Python code wrapped in ```python and ```
    markers
- Ensure the code can run independently
````

G DISCUSSION

G.1 MODEL PERFORMANCE COMPARISON

Comparison 1 For the task detailed in Instruction G.1, Figure 23 compares the outputs of several leading models. Our model, PlotCraftor, successfully generates a visualization that meets all specified requirements. In contrast, the base model, Qwen3-Coder-30B-A3B, exhibits both chart type and factual errors and uses an unprofessional default gray background. GPT-5 clutters the visualization with excessive legends, gridlines, and text, leading to poor clarity and element overlap. Similarly, GLM-4.5 and Cluade-4.1-Opus produce charts with unpolished gray backgrounds and poor color choices, with the latter also failing on chart type compliance. Gemini-2.5-Pro fails to generate any output, resulting in a blank image.

Instruction G.1: Comparison - 1

```
Create a comprehensive temporal analysis of Kaggle tweet
   engagement patterns from 2010-2021. Design a 2x2 subplot
   grid where each subplot combines multiple visualization
   elements: (1) Top-left: A line chart showing yearly tweet
   volume trends overlaid with a bar chart displaying average
    engagement metrics (likes + retweets) per year, (2) Top-
   right: An area chart depicting the cumulative distribution
    of tweet languages over time with stacked areas for the
   top 5 languages, (3) Bottom-left: A dual-axis plot
   combining a line chart of monthly tweet frequency patterns
    overlaid with a scatter plot showing seasonal engagement
   spikes, and (4) Bottom-right: A time series decomposition
   showing trend, seasonal, and residual components of daily
   tweet activity across the entire dataset period. Each
   subplot should include appropriate legends, annotations
   for significant events or patterns, and use consistent
   color schemes to highlight the evolution of Kaggle's
   social media presence and community engagement over the
   decade.
```

Instruction G.2: Comparison - 2

```
Create a comprehensive 3x2 subplot grid analyzing profit
   margin deviations and pricing strategies across multiple e
   -commerce platforms. Each subplot should be a composite
   visualization combining multiple chart types:

Top row (3 subplots):
1. Left: Create a diverging bar chart showing the deviation of
    each platform's MRP from the average MRP, overlaid with
   error bars representing the standard deviation of pricing
   across different style categories
2. Center: Design a dumbbell plot comparing TP1 vs TP2 costs
   for different product categories, with a secondary y-axis
   line plot showing the profit margin percentage deviation
   from the overall average margin
3. Right: Build a slope chart showing MRP changes from "MRP
   Old" to "Final MRP Old" for top 10 style IDs, combined
   with scatter points indicating the magnitude of price
   adjustment

Bottom row (2 subplots):
4. Left: Construct a diverging lollipop chart displaying how
   each platform's MRP deviates from the baseline Amazon MRP,
    with horizontal reference lines showing +=10% and +=20%
   deviation thresholds
5. Right: Generate a radar chart comparing normalized pricing
   metrics (TP1, TP2, various platform MRPs) for the top 5
   most frequent style categories, overlaid with area fill
   showing the deviation range from the category median

Use a consistent color scheme where positive deviations are
   shown in green tones and negative deviations in red tones.
    Include proper titles, legends, and annotations
   highlighting the most significant deviations. The
   visualization should reveal pricing inconsistencies,
   profit margin variations, and strategic pricing patterns
   across different e-commerce platforms.
```

Instruction G.3: Comparison - 3

```
Create a composite visualization showing the composition of
   cosmetic products by chemical content. Design a subplot
   with two complementary charts: (1) a stacked bar chart
   displaying the top 8 companies by total product count,
   with each bar segment colored by primary category to show
   the product type distribution within each company, and (2)
    a pie chart showing the overall market share of these top
    8 companies based on their total number of reported
   products. Include proper legends, titles, and ensure the
   color schemes are consistent between both charts.
```

Instruction G.4: Comparison - 4

```
Create a comprehensive 3x3 subplot grid analyzing the temporal
    evolution of London Underground station usage from
    2007-2017. Each subplot should be a composite
    visualization combining multiple chart types:

Top row (2007-2009): For each year, create a scatter plot
    showing the relationship between weekday entries and
    annual usage (in millions), with bubble sizes representing
    weekend activity levels (Saturday + Sunday entries),
    overlaid with a regression line and confidence intervals.

Middle row (2010-2012): For each year, create a dual-axis plot
    combining a histogram of annual usage distribution with a
    KDE curve overlay, and add vertical lines marking the 25
    th, 50th, and 75th percentiles of usage.

Bottom row (2013-2015): For each year, create a combination
    plot showing both a box plot of weekday vs weekend entry
    ratios by borough (grouped by top 10 boroughs by station
    count) and overlay violin plots to show the distribution
    density.

Each subplot should include year-specific titles, appropriate
    color schemes that evolve across the timeline, and
    statistical annotations (correlation coefficients for
    scatter plots, percentile values for histograms, and
    median values for box plots). The overall visualization
    should reveal how station usage patterns, distributions,
    and borough-level variations evolved during this decade.
```

Instruction G.5: Comparison - 5

```
Create a composite visualization showing the temporal
    evolution of CO2 emissions across different countries.
    Design a subplot layout with two complementary charts: (1)
    a line chart displaying CO2 emissions trends over time
    (1990-2020) for the top 3 countries by total emissions,
    and (2) a stacked area chart showing the cumulative
    contribution of these same countries to global CO2
    emissions over the same time period. Both charts should
    highlight how emission patterns have changed over the
    three-decade span and reveal which countries have been the
    dominant contributors to global CO2 emissions.
```

Comparison 2 The task in Instruction G.1 requires a sophisticated 3x2 grid with composite charts (3 subplots for top row and 2 for bottom row). As shown in Figure 24, PlotCraftor correctly renders this complex layout. The other models struggle significantly: Qwen3-Coder-30B-A3B implements an incorrect layout and suffers from extensive element overlap. GPT-5 produces plots with distorted aspect ratios, awkward typography, and significant text overlap. GPT-oss-120B also fails to generate the correct 3x2 layout. While Cluade-4.1-Opus generates a mostly correct visualization, it misplaces the legend, affecting the overall composition. Gemini-2.5-Pro again produces a blank image.

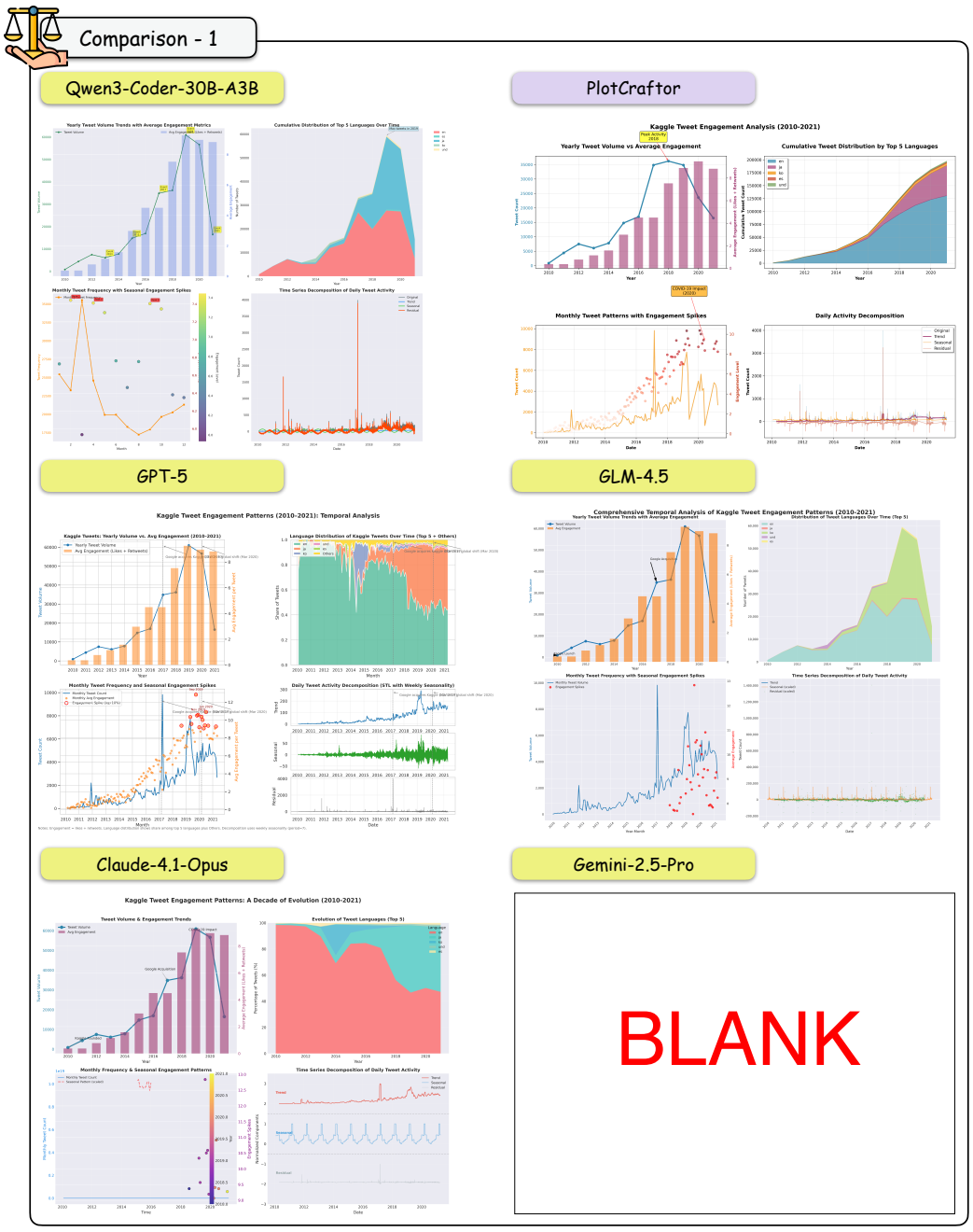


Figure 23: Qualitative comparison for the task in Instruction G.1. PlotCraftor produces a correct and complete visualization, while other models exhibit a range of failures, including incorrect chart types (Qwen3-Coder, Cluade-4.1-Opus), excessive clutter (GPT-5), poor formatting (GLM-4.5), and a blank output (Gemini-2.5-Pro).

Comparison 3 The task in Instruction G.1, which requires a simpler composite chart, demonstrates that many high-performing models can handle less complex requests. As seen in Figure 25, PlotCraftor, Kimi-K2, Cluade-4-Sonnet, and Qwen3-Coder-480B-A22B all produce satisfactory results. This comparison highlights the specific failure modes of other models on what should be a manageable task: Qwen3-Coder-30B-A3B uses an incorrect chart type, while GPT-5 fails to produce any visualization.

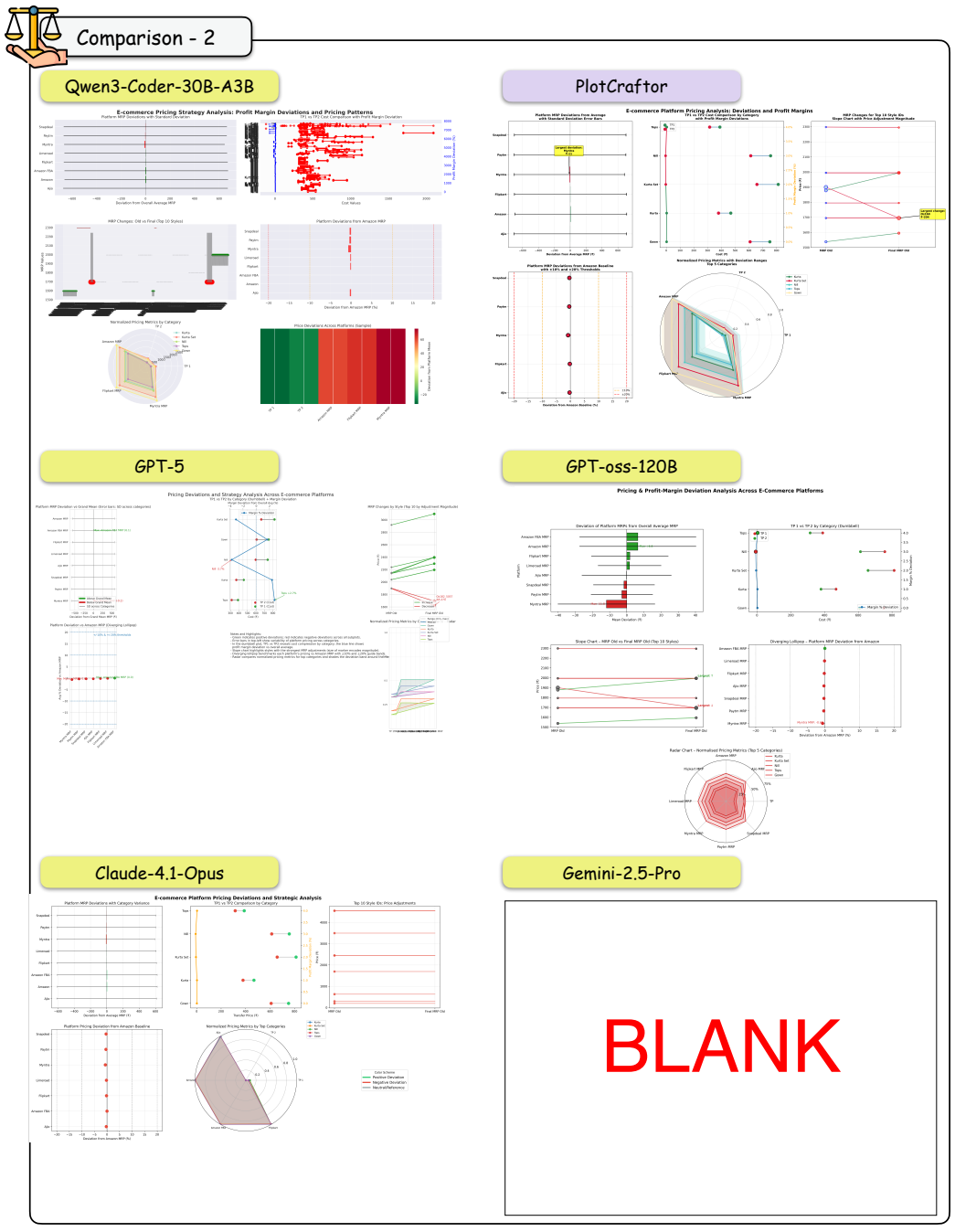


Figure 24: Qualitative comparison for the task in Instruction G.1. PlotCraftor correctly generates the complex 3x2 composite grid, whereas other models fail on layout generation (Qwen3-Coder, GPT-oss-120B), produce distorted outputs (GPT-5), have minor compositional flaws (Cluade-4.1-Opus), or fail completely (Gemini-2.5-Pro).

Comparison 4 For the demanding 3x3 temporal grid specified in Instruction G.1, Figure 26 shows that PlotCraftor is the only model to produce a fully correct visualization. The base model, Qwen3-Coder-30B-A3B, fails to generate any output. The other models, including GPT-5, GLM-4.5, Cluade-4-Sonnet, and Gemini-2.5-Pro, all manage to generate visualizations but fail to adhere to the prompt, exhibiting various chart type errors across the subplots.

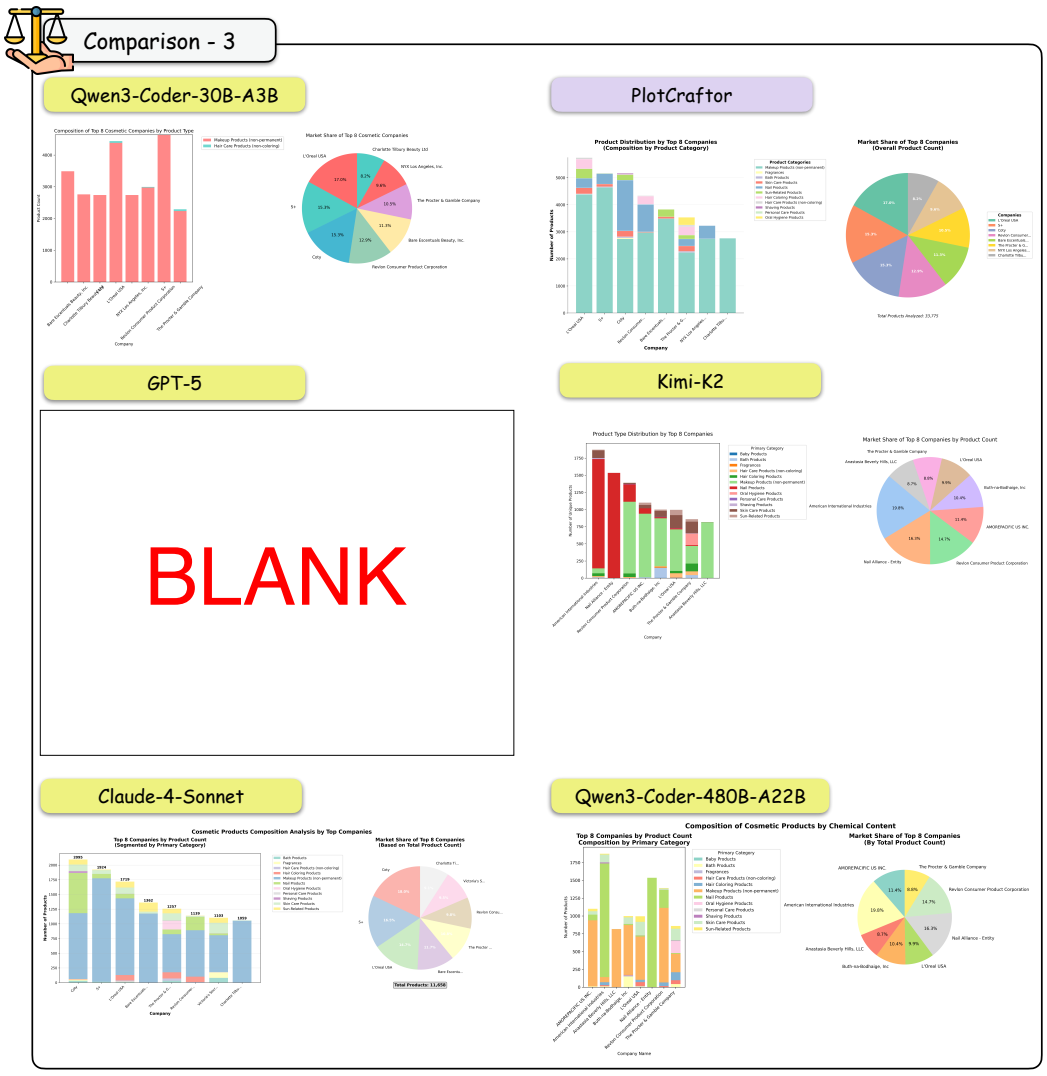


Figure 25: Qualitative comparison for the simpler task in Instruction G.1. While PlotCraftor and several other capable models generate correct visualizations, this figure highlights key failures, including an incorrect chart type from Qwen3-Coder-30B-A3B and a blank output from GPT-5.

Comparison 5 The task in Instruction G.1 requires a composite plot with line and stacked area charts. Figure 27 illustrates that PlotCraftor successfully generates the required visualization with professional formatting. In contrast, Qwen3-Coder-30B-A3B generates an incorrect chart type, failing to meet the core requirement. GPT-5 produces a visualization that, while functionally similar, suffers from a cramped and poorly organized layout. Other powerful models like ChatGPT-4o, Cluade-4.1-Opus, and Gemini-2.5-Pro also attempted the task with varying degrees of success and failure as depicted.

G.2 Scaling Comparison

Figure 28 and Figure 29 present scatter plots of average model scores as a function of model size on PlotCraft's Easy and Hard tasks, respectively. These plots visually confirm that the benefits of model scaling are highly dependent on task difficulty. For models under 100B parameters, performance on Easy tasks scales rapidly with size, while performance on Hard tasks remains flat, only improving for models beyond the 100B threshold. This disparity is mirrored in supervised fine-tuning (SFT): smaller models can be fine-tuned to near-proprietary levels on Easy tasks, yet SFT provides minimal

benefit for Hard tasks. This indicates that solving complex visualization challenges may rely more on the emergent reasoning abilities that come with scale than on task-specific fine-tuning.

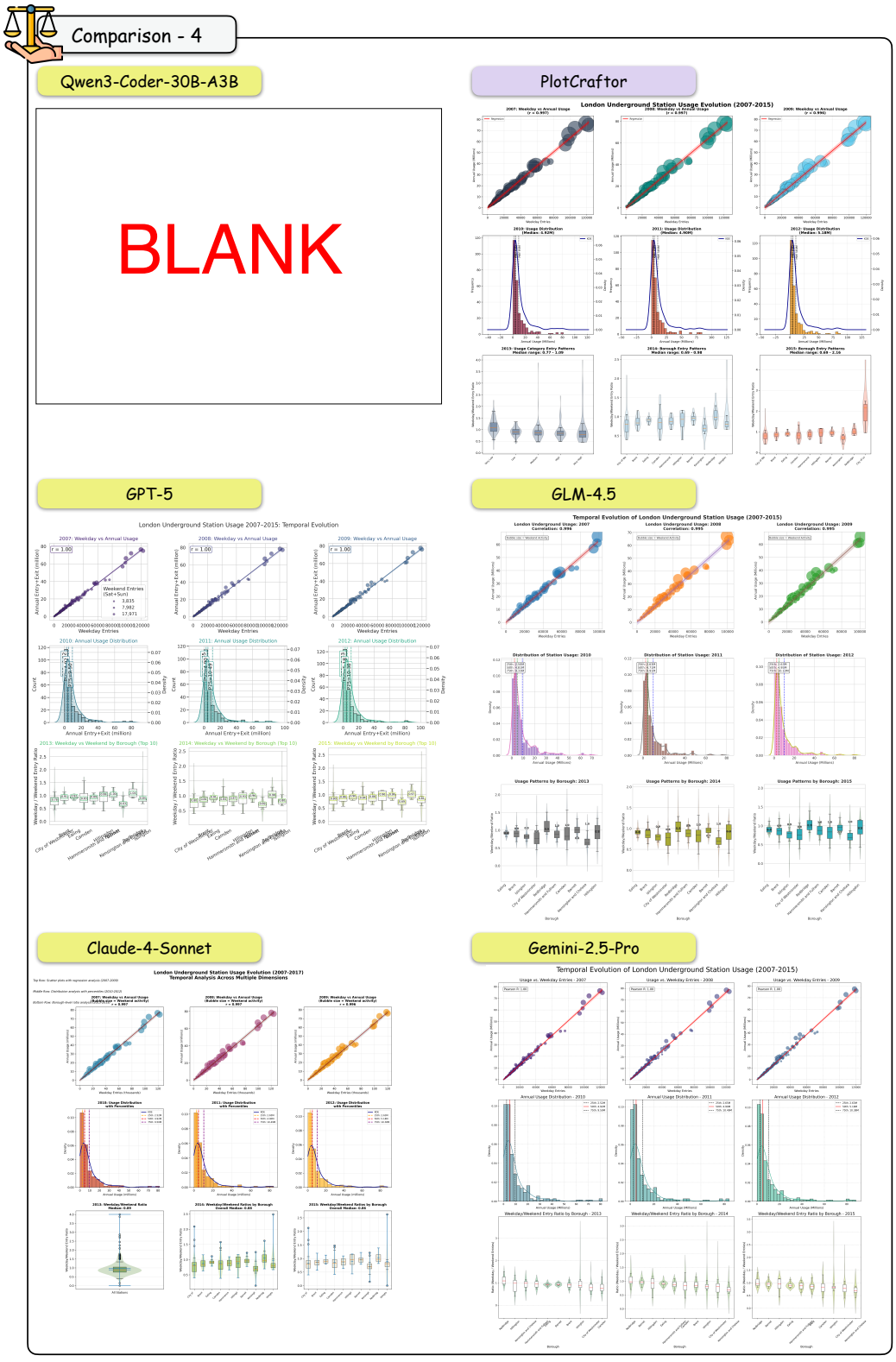


Figure 26: Qualitative comparison for the highly complex 3x3 grid in Instruction G.1. PlotCraftor is the only model to successfully fulfill all requirements. Other models either failed completely (Qwen3-Coder-30B-A3B) or produced visualizations with significant chart type errors (GPT-5, GLM-4.5, Cluade-4-Sonnet, Gemini-2.5-Pro).

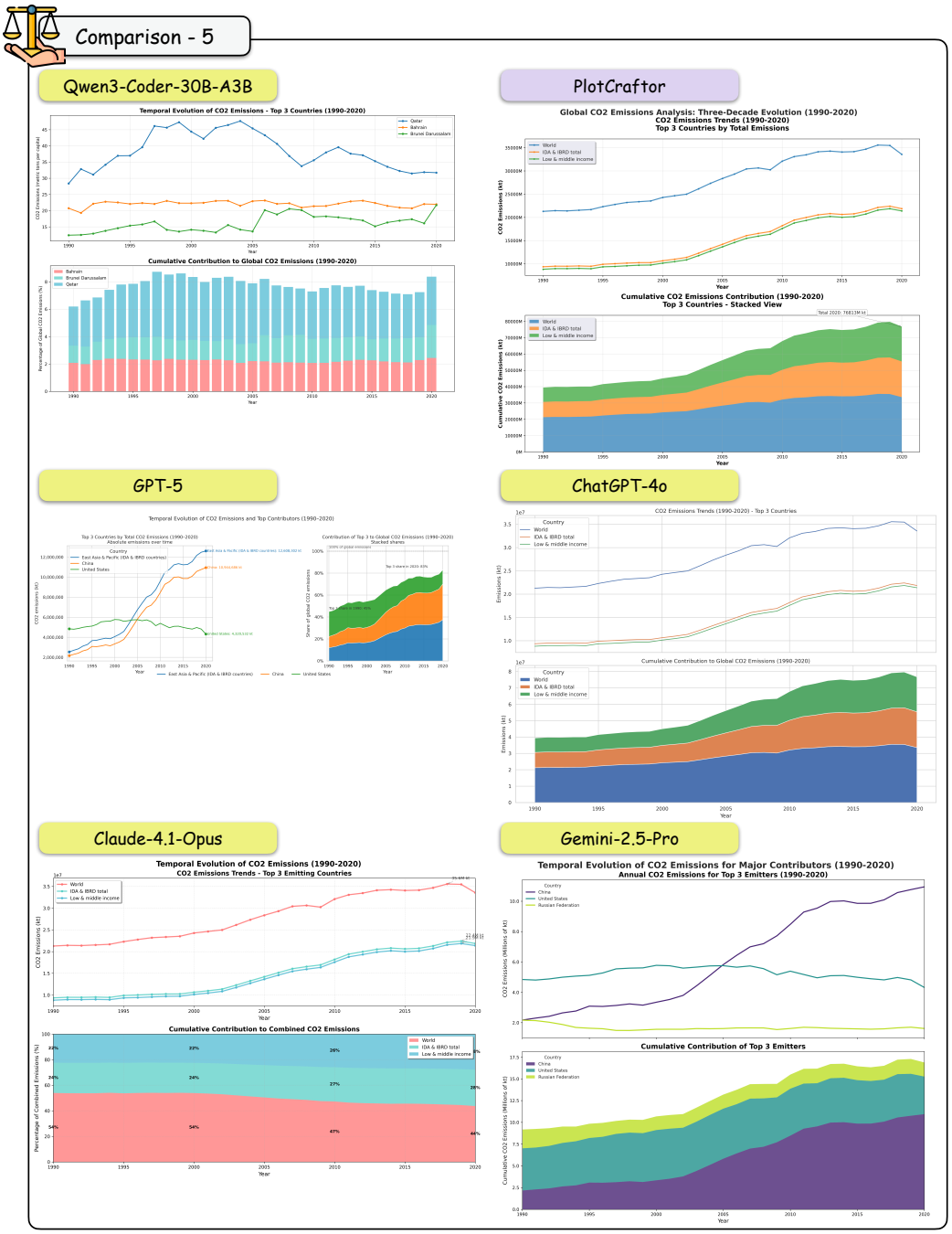


Figure 27: Qualitative comparison for the composite time-series task in Instruction G.1. PlotCraftor's correct and well-formatted output is contrasted with other models that produced incorrect chart types (Qwen3-Coder-30B-A3B) or suffered from poor, cramped layouts (GPT-5).

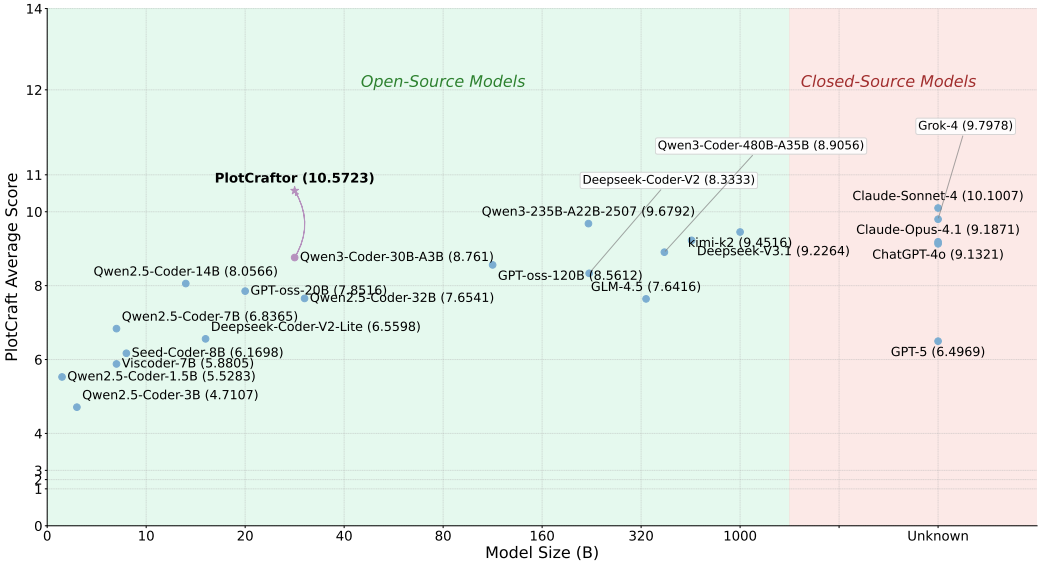


Figure 28: Model performance versus model size on **Easy** tasks from the PlotCraft benchmark. The plot shows a clear positive correlation, where performance scales effectively with the number of parameters across the full range of model sizes.

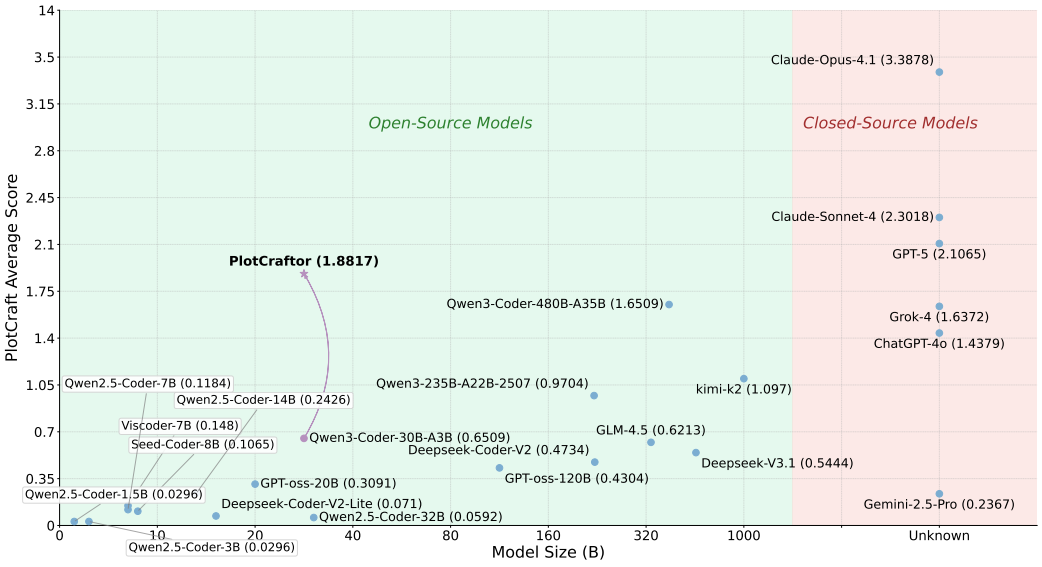


Figure 29: Model performance versus model size on **Hard** tasks from the PlotCraft benchmark. The plot illustrates that performance remains largely stagnant for models under 100B parameters, with a notable improvement only emerging with models that surpass this size threshold.

Compliance Metrics				Quality Metrics				
Layout	Type	Visual	Task	Clarity	Layout	Color	Text	Format
0.61	0.58	0.41	0.50	0.39	0.51	0.63	0.58	0.70

Table 8: Cohen's Kappa scores for agreement between our Claude-4-Sonnet judge and human evaluations, categorized by Compliance and Quality metrics.

Compliance Metrics				Quality Metrics				
Layout	Type	Visual	Task	Clarity	Layout	Color	Text	Format
0.64	0.62	0.53	0.55	0.36	0.52	0.54	0.61	0.67

Table 9: Cohen's Kappa scores for agreement between our ChatGPT-4o judge and human evaluations, categorized by Compliance and Quality metrics.

H Correlation with Human Evaluation Details

In our study, we also evaluated the reliability of other prominent models, Claude-4-Sonnet and ChatGPT-4o, as potential automated judges. The agreement between these models and our human evaluations, as measured by Cohen's Kappa scores, is presented in Table 9 and Table app-tab:gpt-judge, respectively.

The results reveal a consistent and critical weakness in both models' visual analysis capabilities. While they achieve moderate to substantial agreement on most compliance and formatting metrics, their reliability drops sharply on the Clarity metric, which is specifically designed to assess element overlap. With Kappa scores of only 0.39 for Claude-4-Sonnet and 0.36 for ChatGPT-4o on this metric, it is evident that both models struggle to effectively identify and penalize overlapping elements. This deficiency often leads them to assign inaccurately high quality scores to charts with significant readability issues, limiting their viability as standalone judges for complex data visualizations.

I Error Analysis

Error Case 1: Severe Element Overlap

This case demonstrates a critical failure in spatial reasoning, resulting in severe overlap between chart elements and text. As shown in Figure 30, the generated visualization suffers from widespread element occlusion that renders it largely unreadable. Specific failures include: overlapping pie chart labels in subplot (0,1); annotations clashing with the line plot in subplot (0,0); indecipherable stacked text in subplot (0,2); a legend obscuring the plot in subplot (1,0); and a complete overlap of two distinct charts in subplot (1,2). These errors indicate a fundamental inability of the model to manage spatial allocation within a complex multi-plot layout.

Error Case 2: Conflicting Layout Managers

This case illustrates a technical failure where incompatible layout management commands lead to a complete collapse of the plotting canvas. The model-generated code produces a blank image because of a conflict between Matplotlib's `constrained_layout` engine and the subsequent addition of figure-level elements, particularly `fig.legend()`.

The core of the issue lies in the subplot initialization:

```
fig, (ax_top, ax_bottom) = plt.subplots(
2, 1, figsize=(12, 16), sharex=True, \texttt{constrained\_layout=
    True},
gridspec_kw=dict(height_ratios=[1, 1])
)
```

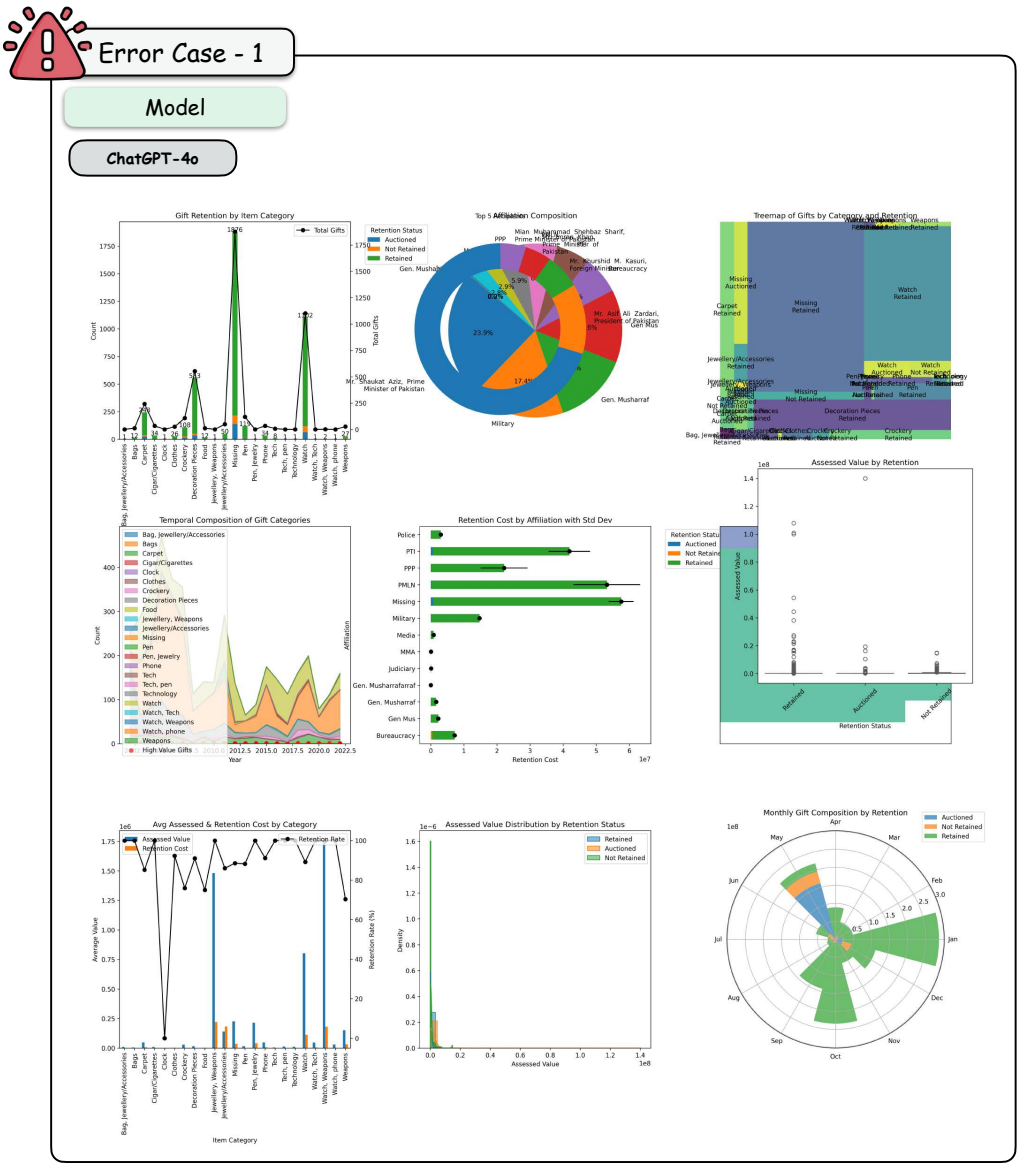


Figure 30: An error case generated by **ChatGPT-4o**, characterized by severe and pervasive element overlap. The visualization fails due to multiple instances of text, labels, legends, and entire subplots occluding one another, making the chart uninterpretable and highlighting a deficiency in layout management.

Here, `constrained_layout=True` activates a sophisticated automatic layout engine designed to prevent the overlap of axes labels and titles by adjusting subplot positions. However, this engine has known limitations when interacting with elements added directly to the figure canvas, such as:

```
fig.suptitle(...)
fig.text(...)
fig.legend(...)
fig.text(...)
```

The conflict arises because `constrained_layout` is primarily designed to manage subplots (Axes) and their immediate decorations. It cannot properly account for the space consumed by figure-level objects like `fig.legend()`, which are placed in the figure's coordinate system independently of the subplot grid.

The failure proceeds as follows:

1. **Engine Activation**: `constrained_layout=True` instructs Matplotlib to manage all subplot layouts automatically.
2. **Content Preparation**: The plotting functions successfully prepare the bar charts and text within the `ax_top` and `ax_bottom` axes objects in memory.
3. **Conflict Introduction**: The code then adds a `fig.legend()` directly to the figure. The layout engine does not natively know how to reserve space for this object while also optimizing the subplot positions.
4. **Layout Calculation Failure**: When `plt.show()` is called, the rendering backend executes the `constrained_layout` algorithm. It attempts to find a solution that accommodates the subplots, their labels, and the "external" figure-level elements. Unable to converge on a stable solution, the algorithm fails.
5. **Canvas Collapse**: A common outcome of this failure is that the layout engine allocates zero (or a near-zero) height and width to the subplots in a misguided attempt to make space for the other elements. Consequently, the primary drawing areas vanish.

The final rendered output is a blank figure canvas. While the figure title or legend might be present, the core subplots are invisible because their dimensions have been reduced to zero, as shown in Figure 31.

Error Case 3: Critical Rendering and Layout Failures This case, generated by Gemini-2.5-Pro, demonstrates a combination of critical rendering failures and severe layout issues that render the chart unusable, as shown in Figure 32.

The most significant issue is a rendering failure in the main plot, which displays as a solid gray area instead of the intended visualization, indicating a fundamental error in the code's data-to-visual mapping. In addition to this critical failure, the chart suffers from severe clarity problems. All x-axis tick labels are collapsed and stacked on top of one another, making them completely illegible. Furthermore, the legend in the supplementary plot overlaps with the chart's content, obscuring key information and making that part of the visualization difficult to interpret.

Reference Visualization for Error Case 3 Figure 33 displays the ground truth for the task previously shown in Figure 32. Unlike the model's output, which suffered from severe overlapping, the reference code achieves a clean and readable layout by strategically selecting top cities based on the data description. This demonstrates that the layout issues were due to the model's lack of reasoning capability rather than task infeasibility.

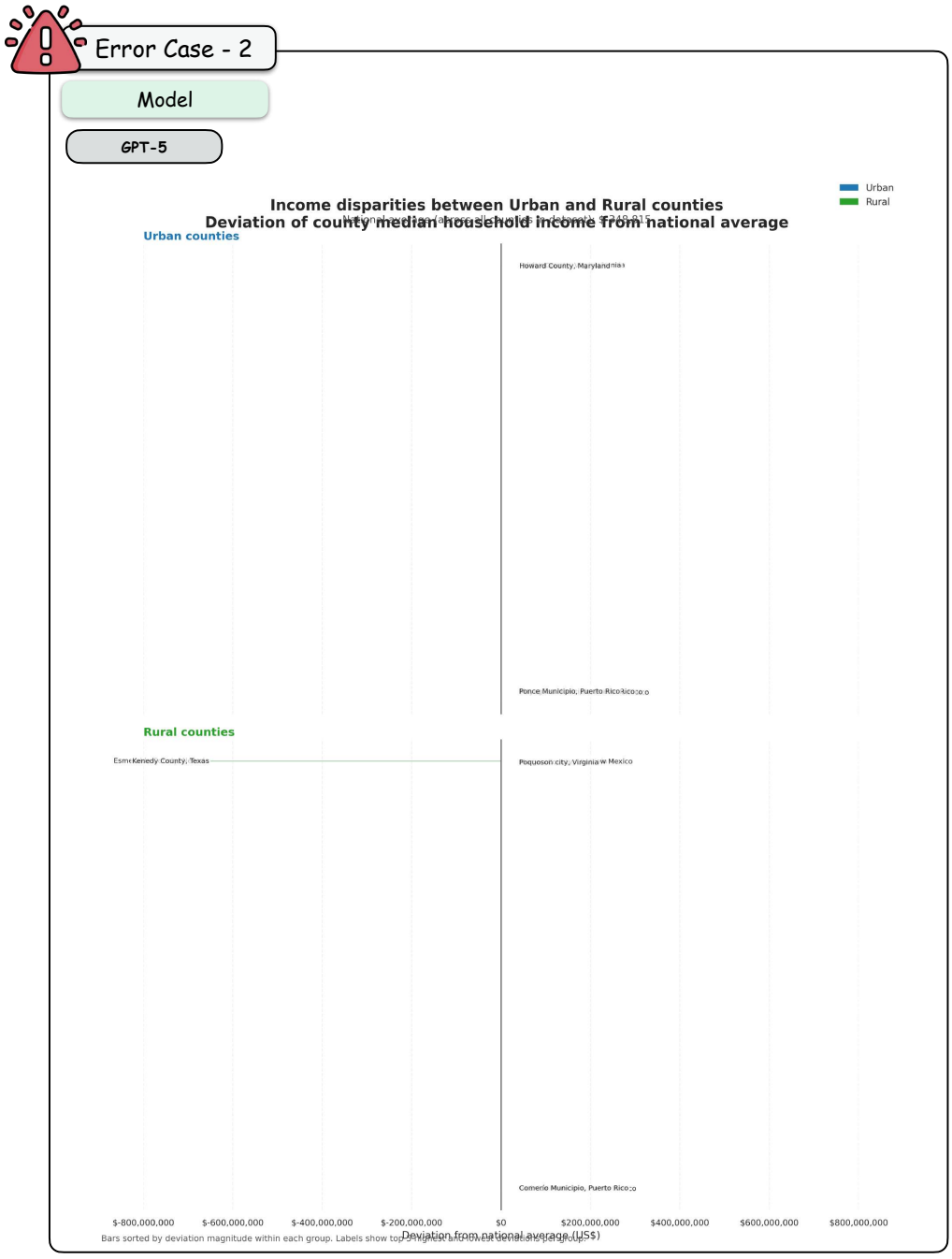


Figure 31: A failure case generated by **GPT-5**, resulting from a conflict between Matplotlib's layout managers. The use of `constrained_layout=True` in conjunction with figure-level elements like `fig.legend()` causes the layout engine to fail, collapsing the subplot dimensions to zero and producing a blank image.

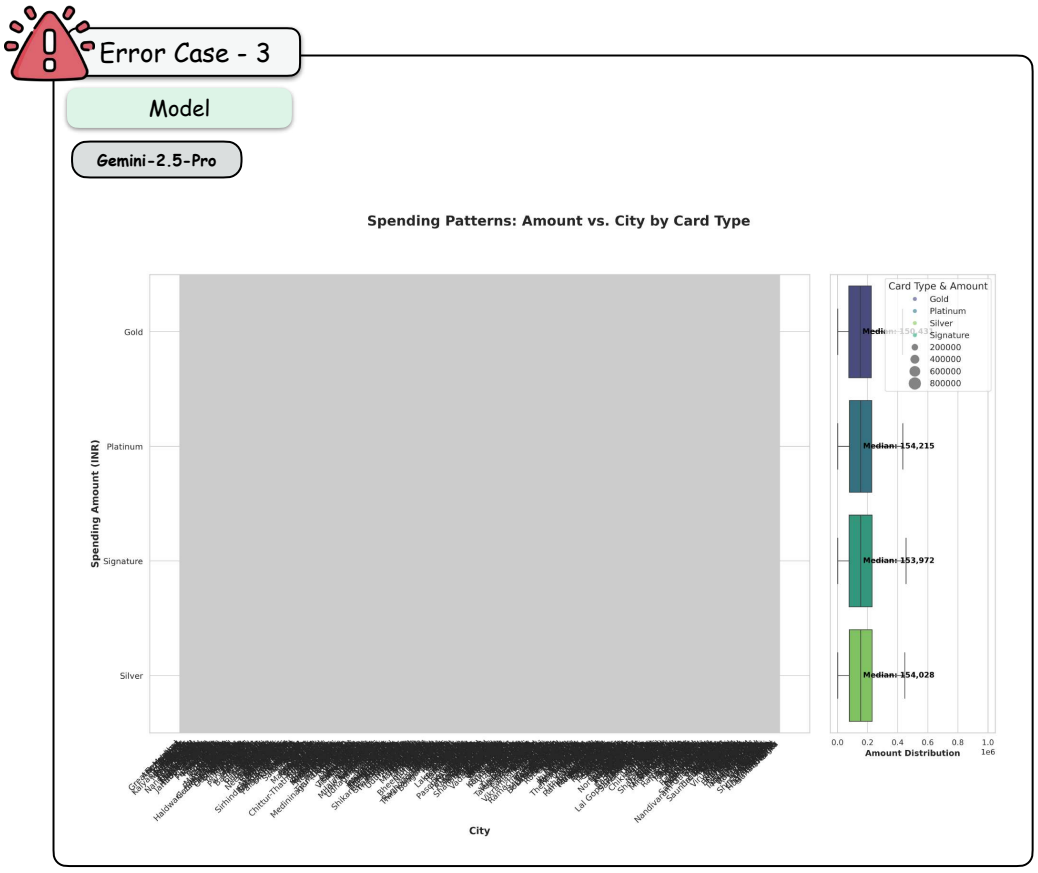


Figure 32: An error case generated by **Gemini-2.5-Pro** exhibiting both a critical rendering failure and severe layout issues. The main plot is incorrectly rendered as a solid gray block, while overlapping x-axis labels and legends make other parts of the visualization unreadable.

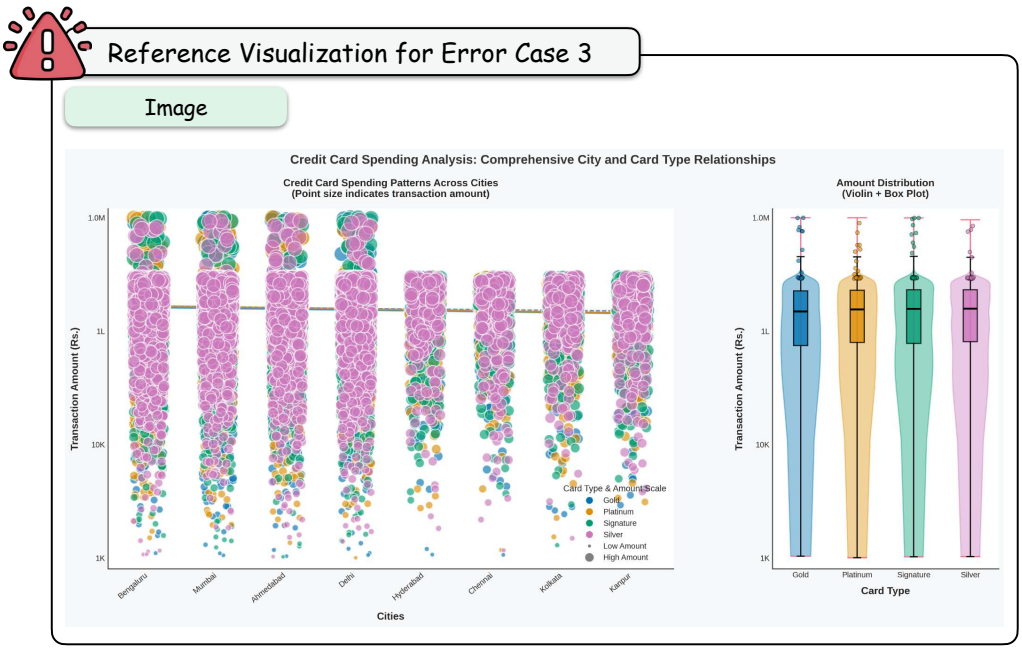


Figure 33: Human-written reference visualization for Error Case 3.

MLLM Judge Failed Case 1

Image

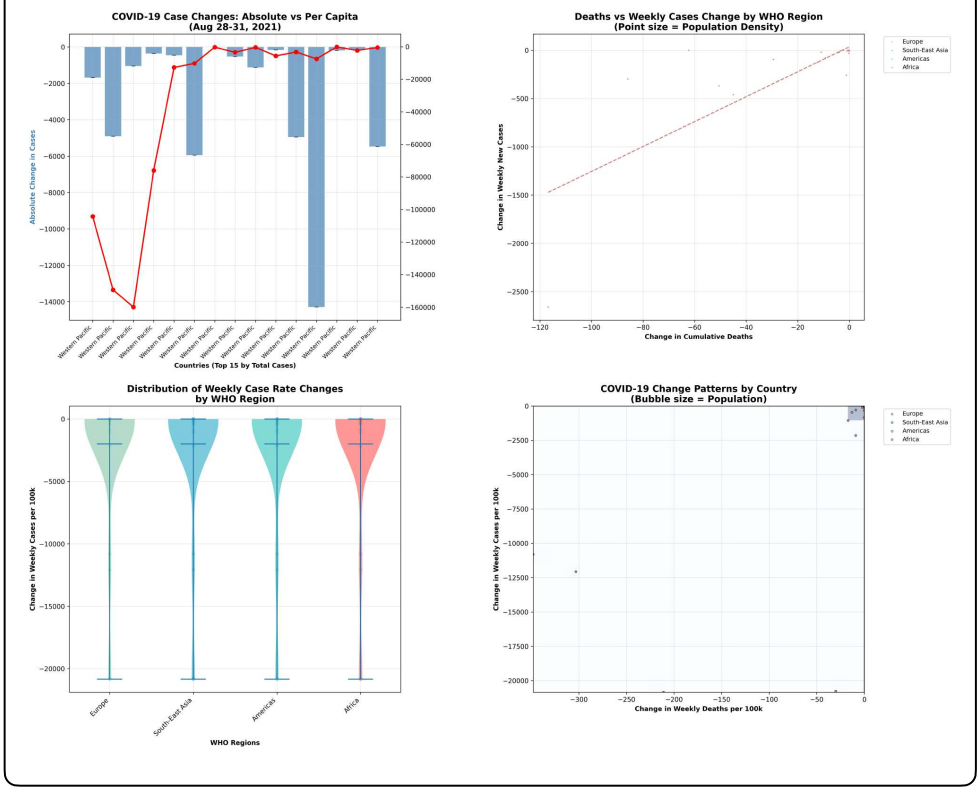


Figure 34: MLLM visual judge failed case 1

Table 10: **Quantitative results on PlotCraft across three difficulty settings: Hard, Medium, and Easy.** The presented scores are the average results over 5 independent evals. Task-Comp. and Quality denote the total scores for the Task Compliance (out of a maximum of 4) and Chart Quality (out of a maximum of 10) sub-metrics, respectively. The metrics are presented separately for Single-Turn Generation and Multi-Turn Refinement.

Model	Single-Turn Generation			Multi-Turn Refinement		
	Pass Rate (%)	Task-Comp.	Quality	Pass Rate (%)	Task-Comp.	Quality
HARD						
Closed-source LLMs						
Claude-4.1-Opus (Anthropic, 2023)	64.85	0.79 ± 0.02	2.59 ± 0.01	68.26	0.89 ± 0.01	2.73 ± 0.02
Claude-4-Sonnet (Anthropic, 2023)	46.75	0.59 ± 0.01	1.71 ± 0.03	57.40	0.65 ± 0.04	2.17 ± 0.02
Gemini-2.5-Pro (Team, 2024)	5.33	0.07 ± 0.09	0.17 ± 0.08	28.99	0.29 ± 0.02	1.30 ± 0.11
ChatGPT-4o-Latest (OpenAI, 2023)	34.32	0.31 ± 0.01	1.12 ± 0.03	47.34	0.37 ± 0.05	1.86 ± 0.02
GPT-5 (OpenAI, 2025)	44.97	0.98 ± 0.01	1.12 ± 0.01	53.85	0.98 ± 0.02	2.03 ± 0.01
Open-source LLMs						
Kimi-K2 (Team et al., 2025b)	29.70	0.28 ± 0.01	0.82 ± 0.06	32.93	0.40 ± 0.01	1.37 ± 0.01
DeepSeek-V3.1 (DeepSeek-AI & etc., 2024)	11.83	0.14 ± 0.02	0.40 ± 0.00	10.06	0.11 ± 0.03	0.43 ± 0.05
GLM-4.5 (Team et al., 2025a)	15.98	0.18 ± 0.02	0.44 ± 0.04	43.79	0.51 ± 0.01	1.64 ± 0.01
GPT-oss-120B (Agarwal et al., 2025)	12.12	0.12 ± 0.01	0.32 ± 0.02	13.17	0.13 ± 0.03	0.42 ± 0.04
GPT-oss-20B (Agarwal et al., 2025)	8.48	0.10 ± 0.01	0.21 ± 0.02	12.57	0.11 ± 0.01	0.31 ± 0.03
Seed-Coder-8B (Seed et al., 2025)	3.55	0.02 ± 0.00	0.08 ± 0.02	37.28	0.30 ± 0.01	1.22 ± 0.01
VisCoder-7B (Ni et al., 2025)	5.33	0.02 ± 0.00	0.13 ± 0.00	50.30	0.38 ± 0.01	2.04 ± 0.01
Qwen3-Coder-480B-A35B (Hui et al., 2024)	39.64	0.48 ± 0.02	1.17 ± 0.06	56.21	0.63 ± 0.01	1.98 ± 0.07
Qwen3-Coder-30B-A3B (Hui et al., 2024)	19.53	0.18 ± 0.01	0.47 ± 0.02	56.80	0.50 ± 0.01	1.76 ± 0.06
PlotCraftor-30B-A3B (Ours)	36.09	0.43 ± 0.01	1.45 ± 0.01	54.44	0.63 ± 0.01	2.11 ± 0.01
MEDIUM						
Closed-source LLMs						
Claude-4.1-Opus (Anthropic, 2023)	72.33	1.97 ± 0.02	4.01 ± 0.02	82.61	2.06 ± 0.02	5.20 ± 0.02
Claude-4-Sonnet (Anthropic, 2023)	72.39	1.58 ± 0.02	3.39 ± 0.02	85.89	1.96 ± 0.02	4.74 ± 0.02
Gemini-2.5-Pro (Team, 2024)	39.26	1.04 ± 0.01	1.77 ± 0.01	67.48	1.74 ± 0.02	4.07 ± 0.02
ChatGPT-4o-Latest (OpenAI, 2023)	65.64	1.48 ± 0.01	2.96 ± 0.02	74.85	1.48 ± 0.02	4.10 ± 0.02
GPT-5 (OpenAI, 2025)	77.30	2.15 ± 0.02	3.29 ± 0.02	80.37	2.04 ± 0.02	4.76 ± 0.02
Open-source LLMs						
Kimi-K2 (Team et al., 2025b)	62.89	1.38 ± 0.01	2.99 ± 0.02	68.94	1.47 ± 0.02	4.05 ± 0.02
DeepSeek-V3.1 (DeepSeek-AI & etc., 2024)	53.99	1.15 ± 0.01	2.54 ± 0.01	42.33	1.01 ± 0.01	2.50 ± 0.01
GLM-4.5 (Team et al., 2025a)	44.17	1.20 ± 0.01	1.96 ± 0.01	68.10	1.50 ± 0.02	3.66 ± 0.02
GPT-oss-120B (Agarwal et al., 2025)	51.57	1.14 ± 0.01	2.13 ± 0.01	32.30	0.76 ± 0.01	1.69 ± 0.01
GPT-oss-20B (Agarwal et al., 2025)	45.91	1.08 ± 0.01	1.94 ± 0.01	36.65	0.93 ± 0.01	1.99 ± 0.01
Seed-Coder-8B (Seed et al., 2025)	28.83	0.60 ± 0.01	1.14 ± 0.01	50.31	0.99 ± 0.01	2.50 ± 0.01
VisCoder-7B (Ni et al., 2025)	11.04	0.17 ± 0.00	0.47 ± 0.00	39.88	0.66 ± 0.01	1.92 ± 0.01
Qwen3-Coder-480B-A35B (Hui et al., 2024)	60.12	1.35 ± 0.01	2.63 ± 0.01	82.82	1.66 ± 0.02	4.31 ± 0.02
Qwen3-Coder-30B-A3B (Hui et al., 2024)	53.37	1.07 ± 0.01	2.27 ± 0.01	74.85	1.48 ± 0.02	3.71 ± 0.02
PlotCraftor-30B-A3B (Ours)	68.10	1.72 ± 0.02	3.54 ± 0.02	83.80	1.79 ± 0.02	4.44 ± 0.02
EASY						
Closed-source LLMs						
Claude-4.1-Opus (Anthropic, 2023)	92.26	3.08 ± 0.03	6.10 ± 0.03	94.27	3.29 ± 0.03	7.89 ± 0.03
Claude-4-Sonnet (Anthropic, 2023)	88.68	3.09 ± 0.03	7.01 ± 0.03	93.08	3.11 ± 0.03	7.67 ± 0.03
Gemini-2.5-Pro (Team, 2024)	81.76	2.43 ± 0.02	5.16 ± 0.02	81.76	2.58 ± 0.02	6.18 ± 0.03
ChatGPT-4o-Latest (OpenAI, 2023)	92.45	3.08 ± 0.03	6.06 ± 0.03	86.79	2.73 ± 0.02	6.88 ± 0.03
GPT-5 (OpenAI, 2025)	88.68	2.20 ± 0.02	4.30 ± 0.02	89.31	2.43 ± 0.02	6.34 ± 0.03
Open-source LLMs						
Kimi-K2 (Team et al., 2025b)	89.68	2.99 ± 0.03	6.46 ± 0.03	82.80	2.66 ± 0.02	6.92 ± 0.03
DeepSeek-V3.1 (DeepSeek-AI & etc., 2024)	88.68	2.97 ± 0.03	6.25 ± 0.03	59.75	1.96 ± 0.02	4.69 ± 0.02
GLM-4.5 (Team et al., 2025a)	71.70	2.44 ± 0.02	5.20 ± 0.02	84.28	2.67 ± 0.02	6.60 ± 0.03
GPT-oss-120B (Agarwal et al., 2025)	83.23	2.79 ± 0.02	5.77 ± 0.02	44.59	1.46 ± 0.01	3.59 ± 0.01
GPT-oss-20B (Agarwal et al., 2025)	81.94	2.55 ± 0.02	5.30 ± 0.02	54.14	1.68 ± 0.02	4.25 ± 0.02
Seed-Coder-8B (Seed et al., 2025)	66.67	2.04 ± 0.02	4.13 ± 0.02	84.91	2.57 ± 0.02	6.09 ± 0.03
VisCoder-7B (Ni et al., 2025)	61.64	1.86 ± 0.02	4.02 ± 0.02	65.41	2.00 ± 0.02	5.02 ± 0.02
Qwen3-Coder-480B-A35B (Hui et al., 2024)	85.53	2.92 ± 0.03	5.98 ± 0.03	89.94	3.03 ± 0.03	7.24 ± 0.03
Qwen3-Coder-30B-A3B (Hui et al., 2024)	86.79	2.77 ± 0.02	5.99 ± 0.03	88.68	2.74 ± 0.02	7.23 ± 0.03
PlotCraftor-30B-A3B (Ours)	90.57	3.13 ± 0.03	7.45 ± 0.03	94.34	2.94 ± 0.03	7.85 ± 0.03