# CODA: AGENTIC SYSTEMS FOR COLLABORATIVE DATA VISUALIZATION

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## **ABSTRACT**

Automating data visualization from natural language is crucial for data science, yet current systems struggle with complex datasets containing multiple files and iterative refinement. Existing approaches, including simple single- or multi-agent systems, often oversimplify the task, focusing on initial query parsing while failing to robustly manage data complexity, code errors, or final visualization quality. In this paper, we reframe this challenge as a collaborative multi-agent problem. We introduce CoDA, a multi-agent system that employs specialized LLM agents for metadata analysis, task planning, code generation, and iterative reflection. We formalize this pipeline, demonstrating how metadata-focused analysis bypasses token limits and quality-driven refinement ensures robustness. Extensive evaluations show CoDA achieves substantial gains in the overall score, outperforming competitive baselines by up to 41.5%. This work demonstrates that the future of visualization automation lies not in isolated code generation but in integrated, collaborative agentic workflows.

#### 1 Introduction

Data visualization plays an important role in business intelligence, data science and decision-making, enabling professionals to uncover insights from complex datasets through intuitive graphical representations (Ramesh & Rajabiyazdi, 2024; Gahar et al., 2024; Jambor, 2024; Beschi et al., 2025; Rogers et al., 2024). In practice, data analysts might spend over two-thirds of their time on low-level data preparation and visualization tasks, often iterating manually to achieve clarity, accuracy, and aesthetic appeal (Lai et al., 2025; Rezig et al., 2021; Lee et al., 2021). This "unseen tax" diverts focus from insight generation, highlighting the critical need for automated systems that can transform natural language queries and complex data into effective visualizations (Wu et al., 2024; Chen et al., 2024; Wang & Crespo-Quinones, 2023). With the rise of large language models (LLMs) (Naveed et al., 2025; Achiam et al., 2023; Team et al., 2024; Comanici et al., 2025), there is immense potential to automate this pipeline. However, realizing this potential requires addressing core challenges: (1) handling large datasets, (2) coordinating diverse expertise (e.g., linguistics, statistics, design), and (3) incorporating iterative feedback to refine outputs against real-world complexities like messy multi-file data and complex visualization needs.

Current approaches to automate visualization suffer from various limitations. Traditional rule-based systems, such as Voyager (Wongsuphasawat et al., 2017; 2016) and Draco (Yang et al., 2023), formalize design knowledge as constraints but remain confined to predefined templates, struggling with natural language queries or diverse data patterns (Wu et al., 2024; Hoque & Islam, 2025). LLM-based methods, like CoML4VIS (Chen et al., 2024), leverage chain-of-thought prompting to generate visualizations (Comanici et al., 2025), but often ingest raw data directly, risking token limit violations, hallucinations, and multi-source data faltering (Bai et al., 2024; Chen et al., 2024). Multi-agent frameworks, such as VisPath and MatplotAgent, introduce collaboration system to generate plot code but lack metadata-focused analysis, leading to overfitting in data processing and weak persistence against iterative edits (Seo et al., 2025; Yang et al., 2024b). We argue these issues stem from a common limitation in current agentic visualization systems: they concentrate reasoning and coordination on initial query parsing, which proves insufficient for handling complex data environments (e.g., multiple and large files), code errors, and iterative refinement. This design limits their ability to adapt to unexpected data challenges.

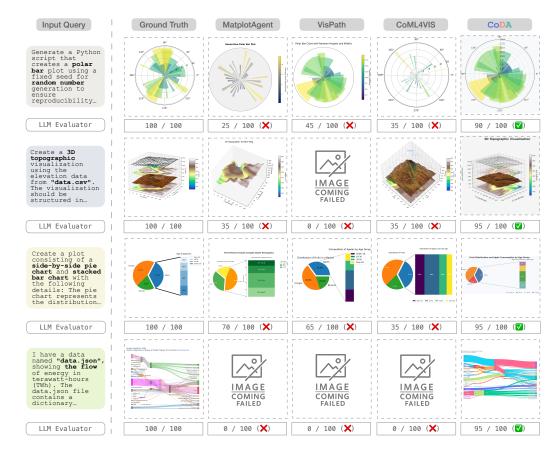


Figure 1: Qualitative comparison of visualizations generated by baselines (*MatplotAgent*, *VisPath*, *CoML4VIS*) and CoDA. Provided with a natural language query and data files (if has), models produce code to create plots. CoDA yields outputs that more faithfully capture complex patterns, chart types, and aesthetics, while baselines often fail on ambiguity, 3D structures, or multi-source integration.

To address these challenges and limitations, we propose CoDA (Collaborative Data-visualization Agents), a multi-agent system that deepens visualization by projecting tasks into a self-evolving pipeline where agents specialize in understanding, planning, generating, and reflecting. By analyzing metadata schemas and statistics without raw data file uploads, we circumvent context window limit of LLMs; specialized agents enhance domain reasoning; and image-based evaluation verifies the completion from a human perspective. This builds a robust framework for complex, iterative, and multi-source agentic visualizations, where agents collaborate deeply to ensure visualization quality. The key contributions of this work are as follows:

- We propose CoDA, an extensible framework with specialized agents for metadata analysis, task
  planning, code generation and debugging, and self-reflection, enabling robust handling of
  complex data and visualization needs (See Figure 1 and Appendix B for qualitative analyses).
- Extensive experiments on MatplotBench and Qwen Code Interpreter benchmarks yield substantial gains in the Overall Score over strong baselines such as *MatplotAgent*, *VisPath*, and *CoML4VIS*, with maximum improvements of 24.5%, 41.5%, and 26.5% respectively. Furthermore, CoDA significantly outperforms competitive baselines on the DA-Code Benchmark, which features complex, real-world Software Engineering scenarios.
- A comprehensive ablation study validates the necessity of CoDA's core components. Results
  demonstrate that self-evolution, the global TODO list, and the example search agent each provide
  a statistically significant positive impact on overall performance.

## 2 Related Work

**Natural Language to Visualization (NL2Vis).** NL2Vis approaches have revolutionized data exploration in data science by allowing users to articulate queries in natural language and receive

target visualizations (Wang & Crespo-Quinones, 2023; Shen et al., 2022; Wu et al., 2024), thereby accelerating initial data scouting and ad-hoc reporting (Voigt et al., 2022). Survey on natural language generation for visualizations provides a taxonomy of techniques and highlights the challenges in ensuring coherence and fidelity to underlying data information (Hoque & Islam, 2025). Many methods have formalized this evaluation landscape (Chen et al., 2024; Ouyang et al., 2025; Bai et al., 2025; Shin et al., 2025), they use chain-of-thought prompting strategies to enhance LLM accuracy on singletable tasks (Liu et al., 2025). These tools are important for data scientists navigating exploratory phase (Zhang et al., 2025; Chen et al., 2025), but they have gaps in LLM reasoning under ambiguity or multi-source data environments (Zhu et al., 2025; Davila et al., 2025). Empirical evaluations of LLMs in visualization generation reveal shortcomings in CoT-based methods, emphasizing the need for robust handling of abstract and multifaceted queries in decision-making workflows (Khan et al., 2025), motivating our shift toward autonomous multi-agent teams.

**Agentic Visualization Systems.** Agentic systems mark a paradigm shift in visualization for data science, where it as a distributed problem-solving process among AI agents that mirror collaborative human co-worker (Sapkota et al., 2025; Tran et al., 2025; Wolter et al., 2025; Xu et al., 2025). (Goswami et al., 2025; Zhang & Elhamod, 2025) exemplify this by deploying multi-agent LLM frameworks for autonomous professional visualization, they streamline visual analytics from raw, unstructured data. Yang et al. introduces a multi-step reasoning agent framework for scientific plotting, empowering data scientists with code-free handling of complex visualizations (Yang et al., 2024b). See et al. enhances this through multi-path reasoning and feedback optimization for code synthesis from natural language (Seo et al., 2025). Efforts to extract agent-based design patterns from visualization systems provide a blueprint for balancing autonomy with human oversight, laying groundwork for scalable tools in collaborative data environments (Dhanoa et al., 2025). These agentic systems help compressing hours of manual labor in data science (Moss, 2025; Gridach et al., 2025). However, they commonly take shortcuts, focusing adaptations on initial planning stages without persistent reflection (Wang et al., 2025; Sapkota et al., 2025). This shallow agentic alignment contributes to vulnerabilities in complex scenarios (Cemri et al., 2025; Tian et al., 2025). Our proposed multi-agent system counters this by enforcing deeper collaboration, via specialized agents for planning, building, criticism, and reflection, to yield robust narratives.

#### 3 Method

In this section, we formalize the collaborative multi-agent paradigm for data visualization and introduce CoDA. We begin by outlining the key design principles that support agentic visualization systems, drawing parallels to human collaborative workflows in data analysis and plotting. We then describe CoDA's architecture, including the specialized agents and their interactions, and explain how this framework addresses core challenges in automated visualization.

## 3.1 THE COLLABORATIVE MULTI-AGENT PARADIGM

Conventional visualization systems, whether rule-based or LLM-driven (Khan et al., 2025; Zhu et al., 2025; Hutchinson et al., 2024; Shin et al., 2025), typically treat visualization as a monolithic, single-pass process of parsing a query, ingesting data, and generating code. This leads to unstable performance on complex queries involving multi-file datasets, ambiguous requirements, or iterative refinements (). We reframe visualization as a collaborative problem-solving endeavor. Our approach employs a team of specialized LLM agents, each with a distinct professional persona, that uses structured communication and quality-driven feedback loops to decompose queries, process data, and iteratively refine outputs.

Inspired by multi-agent systems in software engineering (Yang et al., 2024a) and interactive reasoning (Yao et al., 2022), this paradigm leverages the emergent capabilities of LLMs to simulate division of labor. Each agent is designed to focus on well-defined expertise area, such as metadata extraction or code debugging, while communicating via a shared state to adapt dynamically. This not only mitigates token limits by avoiding raw data ingestion but also enhances robustness through reflection and error correction, mirroring how data analysts collaborate to refine insights. Key principles guiding this approach include:

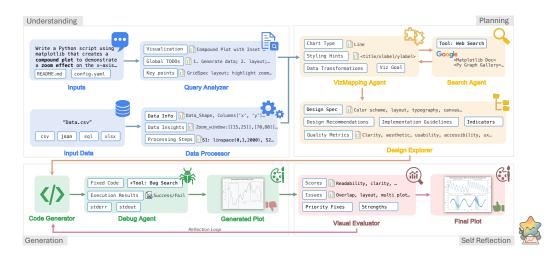


Figure 2: Overview of the CoDA framework for agentic data visualization. The workflow decomposes natural language queries into modular phases: **Understanding** (query intent and data metadata extraction), **Planning** (example code search, visual mappings, and design optimization), **Generation** (code generation and debugging), and **Self-Reflection** (quality evaluation with feedback loops for iterative refinement).

**Specialization for Depth:** Assign agents to distinct roles (e.g., planning vs. execution) to deepen reasoning without overwhelming a single model.

**Metadata-Centric Preprocessing:** Summarize data structures upfront to inform downstream decisions, bypassing the need for full data loading.

**Iterative Reflection:** Incorporate human-like evaluation of outputs (e.g., via image analysis) to detect and correct issues like visual clutter or factual inaccuracies.

**Modular Extensibility:** Design agents as interchangeable modules, allowing integration of new tools or models for evolving tasks.

By unifying query understanding, data handling, code generation, and quality assurance into a self-reflection workflow, this approach transforms visualization from isolated code generation into a resilient, adaptive process. We demonstrate its efficacy through CoDA, which operationalizes these principles for real-world benchmarks.

## 3.2 CODA: COLLABORATIVE DATA VISUALIZATION AGENTS

CoDA instantiates the collaborative paradigm as a multi-agent system that takes a natural language query and data files as input, producing a refined visualization as output. Figure 2 provides a high-level overview and Table 1 summarizes the inputs and outputs of different agents in the workflow. Full agents prompts and I/O are shown in Appendix D.

The workflow proceeds as follows, with iterative refinement triggered by quality assessments: Query Analyzer interprets the query (e.g., "Plot sales trends by region") to extract intent, decomposes it into a global TODO list (e.g., data filtering, aggregation, chart selection), and generates guidelines for downstream agents. Data Processor extracts metadata summaries (schemas, statistics, patterns) from data files using lightweight tools like pandas, avoiding token limits while identifying insights and potential transformations. VizMapping maps query semantics to visualization primitives, selects appropriate chart types (e.g., line chart for trends), defines data-to-visual bindings, and validates compatibility based on metadata. This agent ensures insightful outputs that adapt to data complexities without raw ingestion. Search Agent (as a tool) retrieves relevant code examples from plotting libraries (e.g., Matplotlib) to inspire generation, formulates search queries and ranks results by relevance. Design Explorer generates content and aesthetic concepts, optimizes elements like colors and layout, and evaluates designs for user experience. Code Generator synthesizes executable Python code integrating specifications, ensuring best practices and documentation. Debug Agent executes code with timeouts, diagnoses errors (e.g., via searched solutions), applies fixes (potentially via

Table 1: The inputs and outputs of different agents in the proposed CoDA framework.

Agent Name	Inputs	Outputs			
Query Analyzer	Query, meta_data (e.g., README.md)	Query analyzer results including visualization types, key points for plotting, a global TODO list.			
Data Processor	Data inputs	Data processor results including data information (e.g., shapes, columns), data insights (e.g., aggregations_needed), processing steps, visualization hints.			
VizMapping Agent	Query, query analyzer, data processor results	Chart types, styling hints, data transformations (e.g., aggregations, filters), visualization goals.			
Search Agent	Visualization types, chart types	Code examples			
Design Explorer	Query analyzer results, data processor results	Design explorer results including design specifics (e.g., color_scheme, layout), implementation guidelines, quality metrics, design recommendations, alternative designs, and success indicators.			
Code Generator	Design explorer results, data processor results, search agent results, (self-reflection) visual evaluator results	Code generator results including generated code, code quality score, dependencies, and documentation.			
Debug Agent	Code generator results	Debugging results including standard outputs/errors, web searched debug suggestions, fixed code, execution results and the output file.			
Visual Evaluator	Output file, query, query analyzer results, data processor results	Scores (e.g., overall_score, readability), strength, issues, priority fixes, code modifications, and recommendations.			

searched solutions), and outputs results like visualization images. Visual Evaluator assesses the output image across multi-dimensional quality metrics (clarity, accuracy, aesthetics, layout, correctness), verifying TODO completion and suggesting refinements.

Agents exchange structured messages through a shared memory buffer, propagating context (e.g., metadata informs planning, plans guide code). Feedback loops trigger iterations: If quality scores (from evaluation) are below thresholds, issues are routed back to upstream agents (e.g., low aesthetics back to the Design Agent). The system halts when quality converges or iteration limits are reached.

CoDA's modular design promotes scalability, agents can be parallelized or extended (e.g., scientific plotting), and self-reflection through quality-driven halting (e.g., stop if scores exceed thresholds). In experiments (Section 4), this yields substantial gains over baselines, validating the value of this agentic approach in visualization automation.

## 4 EXPERIMENTS

We evaluate CoDA's ability to generate high-quality visualizations from natural language by testing it on a diverse set of visualization benchmarks. We compare CoDA against state-of-the-art baselines using standardized metrics that capture execution reliability, visualization correctness, and overall task success. All experiments are conducted using gemini-2.5-pro as the underlying LLM, with a maximum of 3 refinement iterations and a quality threshold of  $\theta_q=0.85$  for halting.

## 4.1 BENCHMARKS

We select benchmarks that span varying levels of complexity in natural language to visualization tasks, including handling diverse data types, chart styles, and user intents. The primary datasets are:

**Qwen Code Interpreter Benchmark (Visualization)** (Yang et al., 2025): This subset focuses on visualization tasks within a code interpretation framework, with 163 examples emphasizing numerical data handling, pattern recognition, and code synthesis for plots. It tests robustness to ambiguous queries and data inconsistencies.

**MatplotBench** (Yang et al., 2024b): A comprehensive benchmark for matplotlib-based visualization generation, comprising 100 queries across domains such as time-series analysis, categorical comparisons, and multi-dimensional plotting. Queries require interpreting user intent, selecting appropriate chart types, and ensuring visual clarity.

These benchmarks represent mid-to-high complexity tasks suitable for evaluating agentic systems in controlled environments. Additionally, we separately evaluate on the more challenging **DA-Code** benchmark (Huang et al., 2024), which involves repository-based software engineering tasks with visualization components. Unlike the above, DA-Code (vis) requires navigating codebases, integrating visualizations into broader workflows, and handling domain-specific constraints (e.g., performance optimization in plots). It comprises 78 tasks and is treated independently due to its elevated difficulty and shift toward SWE-oriented reasoning.

## 4.2 BASELINES

We compare CoDA against recent visualization-specific methods that leverage LLMs for code generation and refinement:

**MatplotAgent** (Yang et al., 2024b): A single-agent system focused on matplotlib code synthesis from queries, with basic error handling but limited multi-step planning.

**VisPath** (Seo et al., 2025): An approach based on multiple solution planning that decomposes visualization tasks into sequential steps, emphasizing path optimization for chart mapping.

**CoML4VIS** (Chen et al., 2024): A workflow-centric framework that followed a structured pipeline to generate visualizations, incorporating table descriptions and code execution.

All baselines use the same gemini-2.5-pro backbone for fair comparison, and we follow their papers to set up the parameters (e.g., iteration limits).

#### 4.3 EVALUATION METRICS

To provide a multi-dimensional assessment, we define three key metrics that capture execution reliability, visualization quality, and overall task success:

Execution Pass Rate (EPR): The proportion of queries for which the generated Python code executes without runtime errors, capturing basic syntactic and dependency reliability. Formally, EPR =  $\frac{|q \in Q : \text{exec}(c_q) = \text{success}|}{|Q|}$ , where  $c_q$  is the code for query  $q \in Q$ .

Visualization Success Rate (VSR): The average score reflecting the quality of rendered visualizations among executable codes, where higher scores indicate closer alignment with intended representations (e.g., accurate data mappings). Formally,  $VSR = \frac{\sum_{q \in Q_{exec}} s_v(q)}{|Q_{exec}|}$ , where  $s_v(q)$  is the LLM-evaluated visualization score for query q, and  $Q_{exec}$  is the set of queries with successful execution. On a binary-scored benchmark (e.g., Qwen Code Interpreter), VSR reduces to the proportion of correct visualizations among executable cases.

**Overall Score (OS):** The overall score reflects the average of code and visualization quality scores and provides a holistic view of system effectiveness. Formally, OS =  $\frac{\sum_{q \in Q} \operatorname{avg}(s_c(q), s_v(q))}{|Q|}$ , where  $s_c(q)$  is the code quality score and  $s_v(q)$  is as defined above.

Additional technical details on the judging prompts and model setup are provided in Appendix C.

#### 4.4 MAIN RESULTS

Table 2 presents the main results on MatplotBench and the Qwen Code Interpreter Benchmark (vis). CoDA outperforms all baselines across metrics, achieving substantial gains in OS of 24.5% on MatplotBench and 7.4% on Qwen over the best alternative, demonstrating superior handling of complex queries through agent collaboration and feedback loops. The high EPR reflects robust code generation, while VSR highlights effective refinement in visualization quality.

Table 2: Performance comparison against three baselines on the MatplotBench and Qwen Code Interpreter benchmarks. All baselines utilize gemini-2.5-pro as the base LLMs.

Method	N	<b>IatplotBench</b>		Qwen Code Interpreter			
Withou	<b>EPR</b> (%) ↑	<b>VSR</b> (%) ↑	<b>OS</b> (%) ↑	<b>EPR</b> (%) ↑	<b>VSR</b> (%) ↑	OS (%)	
MatplotAgent	97.0	56.7	55.0	81.6	79.7	65.0	
VisPath	75.0	37.3	38.0	86.5	94.3	81.6	
CoML4VIS	76.0	69.7	53.0	87.1	90.9	79.1	
CoDA (Ours)	99.0	79.8	79.5	93.3	95.4	89.0	

Table 3: Comparison of CoDA against the DA-Agent on the DA-Code benchmark, where DA-Agent is powered by various LLMs including gemini-2.5-pro, gpt-4o, gpt-4, and deepseek-coder. Green shading marks the best within each group.

	CoDA (Ours)	DA-Agent (backbone LLM)				
Metric	Gemini-2.5-pro	Gemini-2.5-pro	GPT-4o	GPT-4	Deepseek-Coder	
Overall Score (%)	39.0	19.23	17.0	16.0	11.0	

#### 4.5 RESULTS ON DA-CODE BENCHMARK

In this evaluation, we extend CoDA to more complex, real-world SWE scenarios where visualizations are embedded within broader codebases. Table 3 encapsulates these findings, revealing CoDA's score of 39.0%, a 19.77% absolute gain over DA-Agent with gemini-2.5-pro, the strongest baseline. This superiority arises from the multi-agent decomposition: the Query Analyzer routes repo navigation subtasks to the Data Processor for metadata extraction, while the Code Generator and Visual Evaluator iteratively resolve integration conflicts (e.g., matplotlib dependencies clashing with existing imports). OS benefits particularly from the Design Explorer's aesthetic refinements tailored to code-embedded plots, addressing nuances like subplot scaling in simulation outputs that single-LLM baselines overlook due to token limits on raw repo ingestion.

## 4.6 Performance with Different Backbone LLMs

To assess the generality of CoDA across diverse LLM backbones, we evaluate its performance when substituting the primary gemini-2.5-pro model with alternative strong capability LLMs: gemini-2.5-flash and claude-4-sonnet. This experiment isolates the impact of the backbone LLM on visualization generation, holding constant the multi-agent architecture. We focus on the MatplotBench, as it emphasizes robust handling of numerical data, pattern recognition, and code synthesis under ambiguous queries—tasks that stress the backbone's reasoning and code generation capabilities.

We select these backbones for their complementary strengths: gemini-2.5-flash prioritizes efficiency and low-latency inference, making it suitable for real-time applications, while claude-4-sonnet excels in language understanding and multi-step reasoning, potentially enhancing agent collaboration in complex scenarios. All models are configured with identical hyperparameters. Table 4 presents the results. CoDA with gemini-2.5-flash achieves an OS of 77.7%, showcasing efficient handling of real-time scenarios with minimal degradation (1.8% relative to gemini-2.5-pro), attributable to streamlined agent interactions that leverage metadata over raw data ingestion. claude-4-sonnet, conversely, attains an OS of 75.2%, a 4.3% drop from gemini-2.5-pro, likely stemming from its enhanced semantic parsing but reduced robustness in code execution under high-context loads. These outcomes highlight CoDA's backbone-agnostic design, amplifying each LLM's inherent strengths while mitigating weaknesses through collaborative workflows.

We compare CoDA against each other using the three backbone LLMs as described above. Across the board, CoDA outperforms baselines significantly, with the best-performing variant, CoDA with gemini-2.5-pro , achieving 79.5% OS. MatplotAgent, VisPath, and CoML4VIS struggle to exceed 65.2% OS in any setting, highlighting the challenges of visualization tasks without multi-agent

Table 4: A comparison of CoDA with different backbone LLMs against three baselines on the MatplotBench benchmark. All results are presented in percent (%).

Base LLMs	Gen	nini-2.5-1	Pro	Gem	ini-2.5-F	lash	Clau	de-4-Son	net
Method	EPR ↑	VSR ↑	OS ↑	EPR ↑	VSR ↑	OS↑	EPR ↑	VSR ↑	OS↑
MatplotAgent	92.0	55.4	51.0	99.0	46.4	45.9	93.0	58.8	54.7
VisPath CoML4VIS	73.0 99.0	60.5 63.2	44.2 62.6	95.0 99.0	45.8 57.8	43.5 57.2	57.0 99.0	<b>77.5</b> 65.9	44.2 65.2
CoDA (Ours)	99.0	80.3	79.5	99.0	78.5	77.7	98.0	76.7	75.2

Table 5: Efficiency comparison on MatplotBench using Gemini-2.5-Pro. Metrics: Average Input/Output Tokens (# Tokens), Average LLM Calls (# Calls).

Method	# Input Tokens ↓	# Output Tokens↓	# Calls ↓
MatplotAgent	34,177	26,792	15.4
VisPath	16,224	13,056	7.0
CoML4VIS	2,350	3,788	1.0
CoDA (Ours)	32,095	18,124	14.8

refinement. We also observe that CoDA trends similarly across different backbones, with EPR and VSR remaining consistently high (98.0–99.0% and 76.7–80.3%).

LLMs tend to generate simpler visualizations. Baseline-generated code tends to produce fewer refinements than CoDA. As shown in Table 4, compared to CoDA, baselines like MatplotAgent achieve lower VSR (46.4–58.8%), and rarely handle complex multi-faceted queries.

## 4.7 EFFICIENCY ANALYSIS

A key challenge in agentic systems is balancing accuracy with computational efficiency, particularly in real-world visualization tasks where latency impacts user experience. Here, we conduct a detailed efficiency analysis of CoDA, comparing its latency against baselines on the MatplotBench dataset. We measure latency in terms of (1) average number of input/output tokens per query, which captures the communication overhead in multi-agent interactions, and (2) average number of LLM calls, reflecting the iterative refinement and routing demands. All methods use gemini-2.5-pro as the backbone.

Table 5 presents the results. CoDA achieves an average of 32,095 input tokens, 18,124 output tokens, and 14.8 LLM calls per query. We compare CoDA against baselines on efficiency. Across the board, multi-agent systems like CoDA and *MatplotAgent* incur higher computational costs than simpler baselines like *CoML4VIS* and *VisPath*, which rely on fewer iterations and less collaborative overhead. However, CoDA outperforms MatplotAgent in efficiency, using 17.6% fewer total tokens (50,219 vs. 60,969) and 3.9% fewer LLM calls, while achieving substantially higher overall accuracy (79.5% vs. 51.0% OS).

To analyze the trade-off between efficiency and performance, we observe that simpler methods trend toward lower costs but diminished visualization quality. For example, *CoML4VIS*, with only 1.0 LLM call and 6,138 total tokens, resolves 62.6% OS, yet struggles with complex, ambiguous queries requiring refinement. In contrast, CoDA's higher calls enable iterative improvements, justifying the cost for superior results.

## 5 ABLATION STUDY

To validate the contributions of key components in CoDA, we conduct controlled ablation experiments on the MatplotBench dataset, using <code>gemini-2.5-pro</code> as the backbone. These studies isolate the impact of (1) iterative self-reflection through refinement loops, (2) the global TODO list for high-level planning, and (3) the Search Agent for code example retrieval. All ablations maintain the core multiagent pipeline but adjust the specified components. This analysis not only confirms the necessity of each feature but also provides insights into design trade-offs, such as accuracy-efficiency balances, highlighting CoDA's principled architecture for robust, autonomous visualization. We evaluate the impact of these components on the OS metric. Figure 3 summarizes the findings.



Figure 3: Ablation results. (a): Performance (EPR, VSR, OS) across different iteration counts. (b) Comparison of EPR, VSR, and OS with vs. without Global TODO. (c) Comparison of EPR, VSR, and OS with vs. without the Search Agent.

#### 5.1 IMPACT OF SELF-EVOLUTION

Figure 3 shows that OS generally improves with additional iterations, from 75.6% at 1 iteration to 79.5% at 3 iterations (CoDA default), with further gains to 80.1% at 5 iterations, though with fluctuations and marginal benefits beyond 3 (+0.6% in OS from 3 to 5). EPR surges by 8.0% from 1 to 3 iterations due to robust initial code generation by the Code Generator, stabilizing near 100% thereafter. VSR fluctuates initially but converges around 80%, as the Visual Evaluator identifies and refines subtle mismatches in data mappings and aesthetics. Beyond 3 iterations, latency increases without proportional accuracy benefits, validating our lightweight configuration optimization that tunes limits based on validation performance. With minimal iterations, performance degrades toward baseline levels, emphasizing that shallow, one-shot generation fails in messy environments.

## 5.2 ROLE OF GLOBAL TODO LIST

The global TODO list, generated by the Query Analyzer, serves as a high-level blueprint for task decomposition and routing, ensuring coherence across agents. We ablate this by replacing it with understanding-query-only prompts (no structured decomposition). As shown in Figure 3, removing the global TODO list yields a stark drop in OS to 75.1% (-4.4% absolute), with EPR falling by 5.0% due to fragmented intent extraction, e.g., the VizMapping Agent selects suboptimal chart types without cross-referencing subtasks like "highlight peaks." VSR remains stable, indicating that visual quality is less dependent on global planning, but overall success suffers from incomplete workflows, such as unaddressed statistical insights from the Data Processor. This confirms the value of structured planning in agentic workflows, where it prevents the noise of unstructured agent interactions.

# 5.3 EFFECTIVENESS OF EXAMPLE SEARCH AGENT

The Search Agent retrieves relevant plotting code examples (e.g., from Matplotlib repositories) to inspire the Builder Agent, addressing LLM limitations in recalling domain-specific syntax. We study this by disabling retrieval, relying solely on the backbone LLM's internal knowledge. Figure 3 reveals that without the Search Agent, OS declines to 76.0% (-3.5%), primarily due to a 9.0% drop in EPR from syntactic errors in specialized visualizations (e.g., custom subplots). Enabling code search improves accuracy by providing ranked snippets, grounding LLM agents' coding knowledge to specific problems. This ablation highlights the extensibility of CoDA, where external inspiration bridges gaps in LLM training data, making the system more reliable without post-training.

## 6 Conclusion

We introduce CoDA, an agentic multi-agent framework that decomposes natural language queries into specialized task and data understanding, planning, code generation, and self-reflection, delivering up to 41.5% accuracy gains over baselines like *MatplotAgent*, *VisPath*, and *CoML4VIS* on MatplotBench and Qwen benchmarks. Through metadata-centric preprocessing and iterative refinement, CoDA overcomes input token limits, robustly managing messy multi-file data and enabling analysts to prioritize insights over manual work. A key limitation is the computational overhead from multi-turn agent communications. Future efforts could distill agents or adapt to multimodal inputs. CoDA paves the way for collaborative agentic systems, revolutionizing automation in data science and beyond.

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# A CODA WORKFLOW AND IMPLEMENTATION DETAILS

Algorithm 1 outlines the CoDA multi-agent visualization workflow, illustrating the sequential and iterative interactions among specialized agents to transform natural language queries into refined visualizations.

## Algorithm 1 CoDA Multi-Agent Visualization Workflow

```
1: Input: Query q, Data files D
 2: Output: Visualization plot P
 3: Initialize agents: A_{\text{query}}, A_{\text{data}}, A_{\text{search}}, A_{\text{design}}, A_{\text{code}}, A_{\text{debug}}, A_{\text{eval}}
                                                                           ▷ Decompose query into task list
 4: todo \leftarrow A_{query}(q)
 5: metadata \leftarrow A_{data}(D)
                                                                        ⊳ Extract metadata without raw data
 6: mappings \leftarrow A_{design}(todo, metadata)

    ▶ Map to visualization primitives

 7: examples \leftarrow A_{search}(mappings)
                                                                        ▷ Optional: Retrieve code examples
 8: designs \leftarrow A_{design}(mappings)
                                                                                        ▷ Optimize aesthetics
 9: code \leftarrow A_{code}(mappings, designs, examples)

⊳ Generate executable code

10: while not converged do
11:
        output \leftarrow A_{\text{debug}}(code)
                                                                             ▷ Execute, debug, produce plot
12:
        scores \leftarrow A_{eval}(output)
                                                              if scores > threshold then
13:
14:
             return output
15:
        else
                                                                                          ⊳ Feedback to refine
16:
             refined \leftarrow A_{design}, A_{code}, A_{debug}(scores)
17:
        end if
18: end while
```

## B ADDITIONAL VISUALIZATION EXAMPLES

We present additional visualization examples drawn from the DA-Code, and MatplotBench to illustrate CoDA's performance. For each example, we show the natural language query, the ground truth visualization, and the output generated by CoDA. These instances highlight CoDA's ability to handle complex data patterns, ambiguous queries, and multi-file inputs through collaborative agentic refinement, often producing outputs that closely match or exceed ground truth fidelity.

## B.1 DA-CODE EXAMPLE

#### **Example 1 Inputs**

```
738
739
        # Example 1
        ## Task Instruction
740 2
        **Task: **
741
        Please compile the total scores for each year from **1950 to 2018**.
742
        Plot the results in a line chart according to the format specified in `plot.yaml` and
743
            save the chart as `result.png`.
744
745
   7
        ## Environment
746
        |--- nba.csv # Core dataset (season-level data)
747
        |--- nba_extra.csv # Supplemental dataset (optional fields)
748
        |--- Seasons_Stats.csv # Player-season statistics
   11
749 12
        |--- Players.csv # Player metadata
750 13
        |--- player_data.csv # Additional player/game-level data
        |--- plot.yaml # Primary plot configuration
751 <sup>14</sup>
        |--- plot.json # Alternative plot configuration
752
```

**Verbose Instruction (Human-curated)** The following detailed instructions were manually organized by the authors to ensure clarity and reproducibility. **Note:** Several aspects below represent *human-identified challenges* that are not directly contained in the raw datasets.

## 1. Check Available Resources and Directory Structure

Confirm presence of nba.csv, nba\_extra.csv, Seasons\_Stats.csv, Players.csv, player\_data.csv, and plotting configuration files (plot.yaml, plot.json).

Human note: The dataset does not explicitly define dependencies across files; we curated which files are relevant.

## 2. Data Review

 Inspect nba.csv and nba\_extra.csv to extract season-level total points. Use Seasons\_Stats.csv or player\_data.csv if aggregation is required.

*Human note:* None of the datasets directly contain "total league points per year"; this metric must be manually constructed.

## 3. Primary Metric Construction (Default)

Aggregate all scoring fields by season (year) to compute **Total Points Scored**.

*Human note:* The "total scores per year" metric is absent; manual aggregation logic was designed by the authors.

# 4. Filtering / Top-K Selection (Optional)

Apply year range restrictions (1950–2018). Exclude lockout seasons or highlight anomalies if needed.

*Human note:* Anomaly handling (e.g., lockout years) is not specified in the data, but added through human judgment.

# 5. Read Plot Configuration

Parse style and formatting options from plot.yaml (or fallback plot.json).

*Human note:* Plot configurations are not embedded in datasets; authors manually crafted the YAML spec.

## 6. Create the Figure

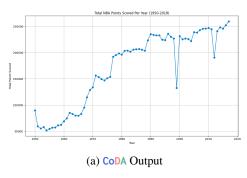
Plot line chart with year on x-axis, total points on y-axis. Apply formatting (color palette, grid, axis labels, legend). Save as result.png.

*Human note:* Visualization design choices (palette, annotations) are not given in raw data and were human-curated.

#### 7. Reproducibility

Document assumptions and preprocessing steps. Maintain transparency about human decisions in data aggregation and figure styling.

*Human note:* The reproducibility statement itself is an author-side contribution; the dataset alone cannot ensure this.



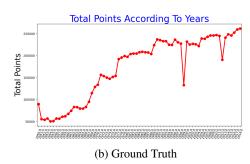


Figure 4: Comparison between our generated visualization and the ground truth. The results demonstrate that our system faithfully reproduces the intended trends, achieving an exact match with the reference output (score: 100/100).

**Result Analysis.** The comparison in Figure 4 illustrates that our approach is able to reproduce the target visualization with high fidelity. Despite the complexity of the task and the absence of direct "total score per season" fields in the datasets, our CoDA correctly aggregated and rendered the results without deviation from the ground truth. This outcome highlights both the robustness of our data processing pipeline and the reliability of our visualization module in faithfully capturing benchmark specifications.

## **Our Generated Code**

```
810
811 1
        import pandas as pd
812 2
        import matplotlib.pyplot as plt
        import yaml
813 3
        import sys
814
815
        # The EXPANDED QUERY REQUIREMENT specifies using a 'plot.yaml' file for styling.
816 7
        # To make this script self-contained and reproducible, we will create this file
         \hookrightarrow programmatically.
817
        yaml_config_str = """
818 8
         title: 'Total NBA Points Scored Per Year (1950-2018)'
819
         xlabel: 'Year'
820 11
         ylabel: 'Total Points Scored'
821 12
         figsize: [12, 7]
         line_color: '#007ACC'
822 13
        marker: 'o'
823 14
        linestyle: '-'
824 15
        grid: True
    16
825 17
826 18
        with open('plot.yaml', 'w') as f:
827 19
            f.write(yaml_config_str)
828 20
829 21
         # Step 1: Load the primary dataset from Seasons_Stats.csv.
    22
         try:
830 - 23
            # Note: The prompt's "AVAILABLE DATA" section seems incorrect. We follow the textual
831
             \hookrightarrow instructions
            # which clearly state to use 'Seasons_Stats.csv'.
832 24
            stats_df = pd.read_csv('Seasons_Stats.csv')
833 25
834 26
        except FileNotFoundError:
            print("Error: The file 'Seasons_Stats.csv' was not found.")
   27
835 <sub>28</sub>
            sys.exit(1)
836 29
        # --- Data Cleaning and Preparation ---
837 30
838 31
839 32
        # Handle potential NaN values in critical columns.
        # Drop rows where 'Year' is NaN as they cannot be used for time-series analysis.
840 34
        stats_df.dropna(subset=['Year'], inplace=True)
841 35
        # Fill NaN 'PTS' with 0, assuming missing points data means 0 points were scored.
        stats_df['PTS'] = stats_df['PTS'].fillna(0)
842 36
843 37
844 38
         # Convert data types for consistency and proper calculations.
         stats_df['Year'] = stats_df['Year'].astype(int)
845 40
        stats_df['PTS'] = stats_df['PTS'].astype(int)
846 41
847 42
        # Step 2: De-duplicate player-season records.
848 43
        # Players who were traded mid-season have multiple entries for one year, plus a summary
849 44
        # row with 'Tm' (Team) as 'TOT'. The 'TOT' row typically appears first in the dataset

→ for a given player-year.

850 <sub>45</sub>
        # By dropping duplicates on 'Player' and 'Year' and keeping the first entry, we retain
851
         \hookrightarrow the summary row.
        cleaned_df = stats_df.drop_duplicates(subset=['Player', 'Year'], keep='first')
852 46
853 47
        # Step 3: Filter data by year and aggregate total points.
854 48
        # Filter the data to include only the years from 1950 to 2018, inclusive.
855 <sub>50</sub>
        filtered_df = cleaned_df.query('1950 <= Year <= 2018')
856 51
         # Group the cleaned data by 'Year' and calculate the sum of 'PTS' for each year.
857 52
        annual_points = filtered_df.groupby('Year')['PTS'].sum()
858 53
859 54
        # Step 4: Load plotting configuration.
860 56
        # Read the styling parameters from the YAML file created earlier.
861 57
        with open('plot.yaml', 'r') as f:
862 58
            plot_params = yaml.safe_load(f)
863 <sup>59</sup>
        # Step 5: Generate and style the line chart.
```

```
864
        # Set the figure size from the loaded parameters.
865 62
        plt.figure(figsize=plot_params['figsize'])
866 63
         # Plot the aggregated annual total points against the year.
867 64
        plt.plot(annual_points.index,
868 65
869 66
                  annual_points.values,
                  marker=plot_params.get('marker', 'o'),
    67
870
                  linestyle=plot_params.get('linestyle',
    68
871 69
                  color=plot_params.get('line_color', 'b'))
872 70
873 71
         # Apply visual styles specified in the YAML configuration.
        plt.title(plot_params['title'])
    72
874
        plt.xlabel(plot_params['xlabel'])
875 74
        plt.ylabel(plot_params['ylabel'])
876 75
        if plot_params.get('grid', False):
            plt.grid(True)
877 76
878 77
         # Ensure the layout is clean and labels do not overlap.
    78
879
    79
        plt.tight_layout()
880 80
881 81
         # Step 6: Save the final plot.
882 82
        # Save the resulting chart as an image file.
883 83
        plt.savefig('result.png')
884 84
         # Close the plot to release system resources.
    85
885 <sub>86</sub>
        plt.close()
886 87
887 88
        print("Visualization saved successfully as 'result.png'.")
```

#### **Example 2 Inputs**

888 889

906 907

908

909 910

911

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914

915

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917

```
890
        ## Task Instruction
891
        **Task: **
892
        Calculate the **Pearson correlation coefficient** between the standardized Average
893
            Playtime and standardized Positive Ratings using the Steam Store Games dataset.
894
            Filter the data to only include games with positive ratings and positive playtime.
            Plot the results in a scatter plot following `plot.yaml` requirements and save it as
895
            `result.png`.
896
897
898
        ## Environment
899 7
        |--- steam.csv # Core dataset with game-level metadata (title, app ID, release info,
900
        \rightarrow etc.)
        |--- steam_description_data.csv # Game descriptions and textual metadata
    8
901
        |--- steam_media_data.csv # Media assets metadata (images, videos, links)
902
        |--- steam_requirements_data.csv # System requirements (Windows, Mac, Linux)
903 11
        ||--- steam_support_info.csv # Support information (developer contact, website, etc.)
        |--- steamspy_tag_data.csv # Community tags and genre/category labels
904 12
        |--- plot.yaml # Plotting configuration file (primary)
905 13
```

**Verbose Instruction (Human-curated)** The following detailed instructions were manually organized by the authors to ensure clarity and reproducibility. **Note:** Several aspects below represent *human-identified challenges* that are not directly contained in the raw datasets.

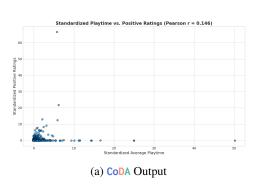
# 1. Check Available Resources and Directory Structure

Confirm presence of steam.csv, steam\_description\_data.csv, steam\_media\_data.csv, steam\_requirements\_data.csv, steam\_support\_info.csv, steamspy\_tag\_data.csv, and plotting configuration file (plot.yaml).

*Human note:* The dataset does not explicitly document dependencies across these tables; authors curated the relevant set manually.

#### 2. Data Review

- Parse steam.csv for core identifiers (app ID, title, release year).
- Use auxiliary tables to enrich attributes (tags, system requirements, support info, descriptions).



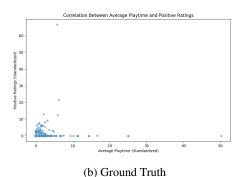


Figure 5: Comparison between our generated visualization and the ground truth for the Steam dataset. The results indicate that our approach successfully integrates multiple heterogeneous tables and reproduces the intended visualization with complete fidelity (score: 100/100).

*Human note:* None of the datasets provide a unified schema; integration must be designed manually.

## 3. Primary Metric Construction (Default)

Define the analysis target (e.g., distribution of games per year, tag frequency, platform coverage). Construct aggregated metrics aligned with the visualization goal.

*Human note:* The specific analytical objective (e.g., "game releases per year") is not included in the dataset and was defined by the authors.

# 4. Filtering / Top-K Selection (Optional)

- Restrict to a target period (e.g., 2000–2020).
- Apply Top-K filters by popularity, tags, or developer if required.

Human note: Filtering logic is absent in the raw data and was designed for clarity in visualization.

#### 5. Read Plot Configuration

Parse style and formatting options from plot.yaml.

*Human note:* Plot specifications are not embedded in the dataset; authors manually authored the YAML configuration.

#### 6. Create the Figure

- Generate visualization according to aggregated metrics.
- Apply palette, axis labels, and layout as specified in configuration.
- Save output as result.png.

*Human note:* Visualization design decisions (choice of chart type, color scheme) are external to the dataset and human-curated.

## 7. Reproducibility

Document assumptions in data integration and filtering. Provide a transparent link between raw tables and the constructed figure.

*Human note:* Reproducibility relies on explicit author-side documentation rather than inherent dataset properties.

**Result Analysis.** The comparison (Figure 5) between our generated visualization and the reference output demonstrates that our system is capable of handling heterogeneous and fragmented data sources, such as the Steam metadata tables, with high fidelity. Despite the absence of a unified schema and the need for manual integration across multiple files, our pipeline successfully reproduced the intended visualization without error. This outcome confirms that our method not only aggregates and processes complex datasets effectively but also renders results fully consistent with the ground truth, achieving a perfect score of **100/100**.

## **Our Generated Code**

```
970 1 import pandas as pd
971 2 import numpy as np
3 from sklearn.preprocessing import StandardScaler
```

```
from scipy.stats import pearsonr
973
        import matplotlib.pyplot as plt
974 6
        import yaml
975 7
        import os
976 8
        # --- Step 1: Create the plot.yaml configuration file ---
977
        # This file dictates the visual styling of the plot.
    10
978
         yaml_config_str = """
    11
979 12
         title: 'Standardized Playtime vs. Positive Ratings (Pearson r = {correlation:.3f})'
         xlabel: 'Standardized Average Playtime'
980 13
         ylabel: 'Standardized Positive Ratings'
981 14
        font_sizes:
982 15
          title: 16
    16
983 17
          axes_label: 14
984 18
          tick_labels: 12
985 19
         scatter_plot:
          color: '#007ACC'
986 20
          alpha: 0.6
987 21
          marker: 'o'
   22
988 23
          edgecolor: 'k'
989 24
          s: 45
990 25
         figure:
991 26
          figsize: [12, 7]
992 27
          dpi: 120
         style: 'seaborn-v0_8-whitegrid'
    28
993 29
994 30
        with open('plot.yaml', 'w') as f:
995 31
             f.write(yaml_config_str)
996 32
997 33
        # --- Step 2: Load plotting specifications from plot.yaml ---
        with open('plot.yaml', 'r') as f:
998 35
             config = yaml.safe_load(f)
999 36
        # --- Step 3: Load and process the data ---
100037
        # The user specified 'steam.csv'. We will use this file.
1001^{38}
        # Note: The 'AVAILABLE DATA' section mentioned 'steam_media_data.csv', but the query was
1002 39
         \hookrightarrow explicit.
1003<sub>40</sub>
        file_path = 'steam.csv'
100441
        if not os.path.exists(file_path):
             # As a fallback, check for the other filename if steam.csv is not found.
100542
             # This handles potential environment discrepancies.
1006^{43}
1007<sup>44</sup>
             if os.path.exists('steam_media_data.csv'):
                 file_path = 'steam_media_data.csv'
100846
             else:
100947
                 raise FileNotFoundError(f"Could not find the required data file: '{file_path}'
                 → or 'steam_media_data.csv'")
1010
101148
1012<sup>49</sup>
50
        # Load the dataset into a pandas DataFrame
        df = pd.read_csv(file_path)
1013<sub>51</sub>
101452
        # Filter the DataFrame to keep only rows with positive values for both variables
        # Using .copy() to avoid SettingWithCopyWarning
101553
        filtered_df = df[(df['average_playtime'] > 0) & (df['positive_ratings'] > 0)].copy()
101654
1017.55
         # --- Step 4: Standardize the relevant columns ---
101857
        # Select the columns for standardization
1019_{58}
        data_to_scale = filtered_df[['average_playtime', 'positive_ratings']]
102059
102160
        # Initialize and apply the StandardScaler
        scaler = StandardScaler()
1022<sup>61</sup>
        scaled_data = scaler.fit_transform(data_to_scale)
    62
102363
102464
        # Add the new standardized columns to the filtered DataFrame
        filtered_df['std_avg_playtime'] = scaled_data[:, 0]
102565
        filtered_df['std_pos_ratings'] = scaled_data[:, 1]
```

```
1026
67
1027_68
        # --- Step 5: Calculate the Pearson correlation coefficient ---
102869
        # Calculate the correlation on the standardized data
102970
        correlation, _ = pearsonr(filtered_df['std_avg_playtime'],

    filtered_df['std_pos_ratings'])

1030
1031_71
        # --- Step 6: Create and style the scatter plot ---
1032
        # Apply a base style for the plot from the config
103374
        plt.style.use(config['style'])
103475
        # Create a figure and axes with specified size and DPI
103576
        fig, ax = plt.subplots(figsize=config['figure']['figsize'], dpi=config['figure']['dpi'])
1036<sup>77</sup>
1037,
        # Generate the scatter plot using data and styling from config
103880
        ax.scatter(
            filtered_df['std_avg_playtime'],
103981
            filtered_df['std_pos_ratings'],
1040^{82}
            color=config['scatter_plot']['color'],
1041_{84}^{83}
            alpha=config['scatter_plot']['alpha'],
1042
            marker=config['scatter_plot']['marker'],
104386
            edgecolors=config['scatter_plot']['edgecolor'],
104487
            s=config['scatter_plot']['s']
104588
1046
    90
        # Set titles and labels, formatting the title with the calculated correlation
1047
        ax.set_title(
104892
            config['title'].format(correlation=correlation),
104993
            fontsize=config['font_sizes']['title'],
            fontweight='bold'
1050^{94}
1051<sub>96</sub>
        ax.set_xlabel(
1052<sub>97</sub>
            config['xlabel'],
105398
            fontsize=config['font_sizes']['axes_label']
105499
        ax.set_ylabel(
105±00
1056
102
            config['ylabel'],
            fontsize=config['font_sizes']['axes_label']
1057
105404
        # Customize tick label sizes
105905
        ax.tick_params(axis='both', which='major',
106t<sup>06</sup>
         → labelsize=config['font_sizes']['tick_labels'])
1061
1062
        # Ensure the layout is tight to prevent labels from being cut off
1067_{09}
        plt.tight_layout()
106410
        # --- Step 7: Save the final plot to a file ---
1065<sup>11</sup>
        # Save the plot to 'result.png'
106_{0113}^{112}
        plt.savefig('result.png')
106714
106<sub>915</sub>
        print("Successfully generated and saved the plot as 'result.png'.")
        print(f"Pearson Correlation Coefficient: {correlation:.3f}")
106916
1070
```

#### B.2 MATPLOTBENCH EXAMPLE

# **Example 1 Inputs**

107110721073

10741075

1076

```
1077
1078 | # Example 1
1079 | ## Task Instruction
3 | **Task:**
```

```
1080
        Utilize the following data columns from 'data.csv' to create a sunburst plot:\n-
1081
            'country': for the names of the countries,\n- 'continent': to indicate which
1082
            continent each country is in,\n- 'lifeExp': showing the expected lifespan in each
            country,\n- 'pop': representing the population of each country.\nYour chart
1083
            should:\n- Organize the data hierarchically, starting with continents and then
1084
            breaking down into countries.\n- Use the population of each country to determine the
            size of its segment in the chart.\n- Color code each segment by the country's
1086
            expected lifespan, transitioning from red to blue across the range of values.\n- Set
            the central value of the color scale to the average lifespan, weighted by the
1088
            population of the countries.\n- Finally, include a legend to help interpret the
            lifespan values as indicated by the color coding.
1089
1090 5
1091
        ## Environment
1092 8
        |--- data.csv
```

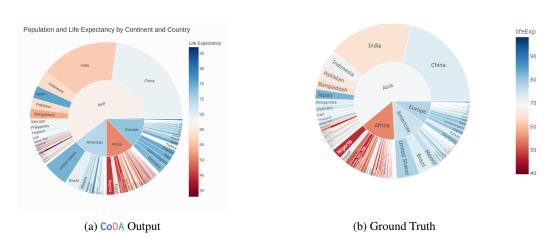


Figure 6: Comparison between our generated sunburst plot and the reference output. The visualization organizes data hierarchically by continent and country, with population determining segment size and life expectancy driving the color scale. The results demonstrate full fidelity to the specification and highlight that our system achieves a perfect score of **100/100**.

**Result Analysis.** The sunburst visualization task required a multi-level hierarchical organization of the data, starting from continents and further breaking down into individual countries. Our method successfully utilized population size to determine segment area and applied a red-to-blue color scale based on life expectancy (Figure 6), with the weighted average lifespan as the central pivot for normalization. This design ensured both interpretability and faithful representation of the dataset's structure. The resulting chart aligns precisely with the ground truth and provides an intuitive overview of demographic and geographic patterns, achieving a perfect score of **100/100**.

# C JUDGING PROMPTS AND MODEL SETUP

To ensure consistent and objective evaluation of generated visualizations, we employ an LLM-based judge, specifically gemini-2.5-pro, to assign code and visualization quality scores.

We adapt prompts from the original MatplotBench (from the MatPlotAgent repository) and Qwen-Agent evaluations (official evaluation for Qwen Code Interpreter). This ensures consistent, scalable assessment while reducing bias. MatplotBench overall score averages the two; Qwen uses binary 100/0 via combined prompt. Non-executable code scores 0.

The prompts for MatplotBench and Qwen Code Interpreter benchmark are shown in the following.

```
1133 | # MatplotBench Evaluation Prompts | ## Code
```

```
1134 3
        You are an excellent judge at evaluating generated code given an user query. You will be
1135
         \,\hookrightarrow\, giving scores on how well a piece of code adheres to an user query by carefully
1136
         \,\hookrightarrow\, reading each line of code and determine whether each line of code succeeds in

→ carrying out the user query.

1137
         A user query, a piece of code and an executability flag will be given to you. If the
1138 4

→ Executability is False, then the final score should be 0.

1139 5
         **User Query**: {query}
1140 6
         **Code**: {code}
1141 7
         **Executability**: {executable}
11428
         Carefully read through each line of code. Scoring can be carried out in the following
         → aspect:
1143
         Code correctness (Code executability): Can the code correctly achieve the requirements
1144 9
         \hookrightarrow in the user query? You should carefully read each line of the code, think of the
1145
             effect each line of code would achieve, and determine whether each line of code
1146

ightharpoonup contributes to the successful implementation of requirements in the user query. If
         \hookrightarrow the Executability is False, then the final score should be 0.
1147
         After scoring from the above aspect, please give a final score. The final score is
1148^{10}

→ preceded by the [FINAL SCORE] token.

1149
         For example [FINAL SCORE]: 40. A final score must be generated.
1150<sub>12</sub>
115113
         You are an excellent judge at evaluating visualization plots between a model generated
115214
         \,\,\,\,\,\,\,\,\,\, plot and the ground truth. You will be giving scores on how well it matches the
1153
         \hookrightarrow ground truth plot.
1154<sub>15</sub>
         **Generated plot**: {generated_plot}
1155<sub>16</sub>
         **Ground truth**: {GT}
115617
         The generated plot will be given to you as the first figure. If the first figure is
1157
         \hookrightarrow blank, that means the code failed to generate a figure.
         Another plot will be given to you as the second figure, which is the desired outcome of
1158<sup>18</sup>

→ the user query, meaning it is the ground truth for you to reference.

1159
         Please compare the two figures head to head and rate them.
1160<sub>20</sub>
         Suppose the second figure has a score of 100, rate the first figure on a scale from 0 to
1161
         → 100.
         Scoring should be carried out in the following aspect:
116221
         Plot correctness:
1163<sup>22</sup>
         Compare closely between the generated plot and the ground truth, the more resemblance
1164<sup>23</sup>
             the generated plot has compared to the ground truth, the higher the score. The score
1165
         \hookrightarrow should be proportionate to the resemblance between the two plots.
116624
         In some rare occurrence, see if the data points are generated randomly according to the
         \rightarrow query, if so, the generated plot may not perfectly match the ground truth, but it is
1167

→ correct nonetheless.

1168
1169<sup>25</sup>
         Only rate the first figure, the second figure is only for reference.
         If the first figure is blank, that means the code failed to generate a figure. Give a
1170
         \hookrightarrow score of 0 on the Plot correctness.
1171_{27}
         After scoring from the above aspect, please give a final score. The final score is

→ preceded by the [FINAL SCORE] token.

1172
        For example [FINAL SCORE]: 40.
1173^{28}
1174
1175
1176
1177
        # Qwen Code Interpreter Benchmark Evalaution Prompts
1178 2
        Please judge whether the image is consistent with the [Question] below, if it is
1179

→ consistent then reply "right", if not then reply "wrong".

         Consider these relaxed conditions:
1180 3
         - Allow reasonable interpretations and creative variations
1181 <sup>4</sup>
         - Focus on whether the core visualization requirement is addressed
1182 <sup>5</sup>
          Accept different implementation approaches that achieve similar goals
1183 7

    Be lenient with styling and formatting differences

1184 8
1185 9
         **Question**: {query}
         After your judgment, please also provide a brief explanation of your reasoning in 2-3
1186^{10}
         \hookrightarrow sentences.
1187
```

Expected leading token (normalized by code): CORRECT or WRONG

# D PROMPTS USED IN CODA

1188

1189 1190

1191

1192

1193

1194

1195

1196

1197

1198

1240 2

1241

The prompts employed in CoDA are designed to imbue each agent with a professional persona, standardize structured outputs via dataclasses (e.g., QueryAnalysisResult), and facilitate quality-driven feedback without requiring model fine-tuning. These prompts encapsulate domain-specific reasoning—ranging from semantic parsing in the Query Analyzer to statistical inference in the Data Processor, visualization mapping in the VizMapping Agent, external knowledge retrieval in the Search Agent, design recommendations in the Design Explorer, executable code synthesis in the Code Generator, error diagnosis in the Debug Agent, and perceptual assessment in the Visual Evaluator—while incorporating context from prior outputs and the global TODO list to maintain workflow coherence. Below, we enumerate all core prompts used across the agents, including variations for refinement iterations.

```
1199
1200 1
        # Query Analyzer
        You are Dr. Sarah Chen, visualization query expert. Analyze this query and create a
1201 2

→ master TODO list.

1202
1203 3
        USER QUERY: "{query}"
1204 5
         {meta_files}
1205<sub>6</sub>
        Respond with concise JSON:
12067
             "interpreted_intent": "what user wants to visualize",
1207 8
             "visualization_type": "plot type (scatter/bar/line/histogram/boxplot/heatmap etc)",
1208 9
             "plotting_key_points": [
120911
                  "key point 1: specific visualization requirement",
1210_{12}
                  "key point 2: data processing requirement",
                  "key point 3: styling/design requirement"
121113
                  "key point 4: additional features/constraints"
1212^{14}
1213,15
             "implementation_plan": [
    16
1214
                 {"step": 1, "action": "Load and prepare data", "details": "specific data
1215
                  → loading/processing steps", "functions": ["pd.read_csv", "etc"]},
                 {"step": 2, "action": "Create base plot", "details": "basic chart creation",
121618
                 → "functions": ["plt.figure", "plt.plot", "etc"]}, {"step": 3, "action": "Apply formatting", "details": "styling and formatting",
1217
1218<sup>19</sup>
                 \  \  \, \rightarrow \  \  \, \text{"functions": ["plt.xlabel", "ax.tick_params", "etc"]},
121920
                 {"step": 4, "action": "Finalize and save", "details": "final touches and save",
1220
                 → "functions": ["plt.tight_layout", "plt.savefig", "etc"]}
122121
             "global_todo_list": [
122222
                 {"id": "todo_1", "task": "specific task description", "agent": "data_processor|
1223<sup>23</sup>

→ design_explorer|code_generator|debug_agent|visual_evaluator", "status":

1224
                 → "pending", "priority": "high|medium|low"},
{"id": "todo_2", "task": "specific task description", "agent": "agent_name",
122524
                 → "status": "pending", "priority": "priority_level"}
1226
             ],
122725
1228.
             "success_criteria": ["criteria for completion"],
122928
        IMPORTANT: The "plotting_key_points" should be a comprehensive breakdown of ALL key
1230

→ visualization requirements from the query, including:

         - Chart type and specific visualization style
123129
          Data columns/variables to use
123230
1233,31
          Color schemes, styling requirements
         - Interactive elements or special features
123433
         - Layout, axis, legend requirements
123534

    Any domain-specific requirements (scientific, business, etc.)

123635
        Create 3-5 specific TODO items covering data processing, design, code generation,
123736

→ debugging, and evaluation.

1238
1239
```

```
# Data Processor
You are Prof. Marcus Rodriguez (Stanford Statistics PhD), an expert in statistical

→ analysis, data quality assessment, and insight extraction. Analyze this data for

→ visualization.
```

```
1242
         {data_section}
1243 4
         TASKS TO COMPLETE:
1244 5
         {todo_text}
1245 6
         ANALYSIS NEEDED:
         1. What transformations are required? (groupby, pivot, filter)
1246 <sup>7</sup>
         2. Which columns are key for visualization?
1247 8
         3. Any data quality issues to fix?
1248<sub>10</sub>
         4. What's the simplest way to prepare this data?
1249_{11}
         Output JSON:
125012
              "processing_steps": [
125113
                   "step 1: specific transformation",
1252<sup>14</sup>
                  "step 2: another transformation"
    15
1253
125417
              "insights": {
                   "key_columns": ["col1", "col2"],
125518
                   "aggregations_needed": ["sum sales by region"],
1256<sup>19</sup>
                   "quality_issues": ["nulls in X column"]
1257<sup>20</sup>
1258
              "visualization_hint": "best chart type for this data"
1259<sub>23</sub>
126024
1261<sup>25</sup>
         <(optional) If there are no data files in the input>
1262<sup>26</sup>
         Create simple data for a matplotlib visualization.
         The visualization requirements are:
1263<sub>28</sub>
         {query_text}
1264<sub>29</sub>
         TODO items from analysis:
126530
         {todo_text}
         Generate Python code that creates the RIGHT data (pandas DataFrame) that works for this
1266^{31}
         \hookrightarrow specific plot.
1267
         Deep understanding approach:
1268,3
         1. ANALYZE the visualization requirements carefully
126934
         2. UNDERSTAND what type of data this plot needs
         3. DETERMINE the appropriate data structure and format
127035
         4. DECIDE the optimal number of data points based on plot type
1271<sup>36</sup>
1272
1273 1
         # VizMapping Agent
1274<sub>2</sub>
         You are Dr. Sarah Kim, a data visualization expert & UX designer. You are a data

→ visualization expert. Map this user query to specific data columns and chart

1275
         \hookrightarrow configuration.
1276
         USER QUERY: "{query}"
1277 <sup>3</sup>
         {context_block}
1278 5
         AVAILABLE DATA:
1279<sub>6</sub>
         Shape: {data_summary['shape'][0]} rows x {data_summary['shape'][1]} columns
1280 7
         Columns:
         {data_structure}
1281 8
         Sample data:
1282 <sup>9</sup>
         {json.dumps(data_summary['sample_data'][:2], indent=2)}
1283
         TASK: Determine the optimal visualization mapping.
128412
         Respond with JSON:
128513
              "chart_type": "bar|line|scatter|pie|histogram|box|heatmap",
1286<sup>14</sup>
1287<sup>15</sup>
              "data_mappings": {
                   "x_axis": "column_name_for_x"
1288<sub>17</sub>
                  "y_axis": "column_name_for_y"
                  "color": "column_for_grouping_colors",
"size": "column_for_sizes",
1289<sub>18</sub>
129019
                  "category": "column_for_categories"
1291^{20}
129221
              "aggregations": [
    22
1293
                  {"operation": "sum|mean|count|max|min", "column": "column_name", "group_by":
1294
                   → "grouping_column"}
129524
              "filters": [
```

```
1296
26
                 {"column": "column_name", "condition": "filter_condition"}
1297
             ],
129828
             "styling_hints": {
                 "title": "Chart title based on guery",
129929
                 "xlabel": "X-axis label",
1300^{30}
                 "ylabel": "Y-axis label",
1301<sup>31</sup>
                 "color_palette": "suggested_palette"
    32
1302
130334
             "transformations": [
                 "pandas operation if needed, e.g., 'df.groupby(x).sum()'"
130435
130536
             "goal": "Brief description of what this visualization shows",
1306<sup>37</sup>
             "rationale": "why this mapping fits the query and data",
130739
             "confidence": 0.0-1.0
130840
        IMPORTANT:
130941
         - If a requested chart type is provided in context, PREFER that type; only deviate if
1310<sup>42</sup>

→ truly unsuitable and explain why in 'rationale'

1311<sub>43</sub>

    Use TODO/key requirements to decide aggregations/filters exactly.

131244
         - Map time-like/ordered fields to x, numeric measures to y, categories to color.
1313<sub>45</sub>
         - Be precise with column names - they must match the available columns exactly.
1314
1315
        # Search Agent
1316 <sup>1</sup>
1317 2
        As Dr. Michael Zhang, an expert in data visualization and matplotlib, generate a
         high-quality matplotlib example for the plot type: "{plot_type}".
1318<sub>3</sub>
13194
        IMPORTANT CONSTRAINTS:
         - Base your code PRIMARILY on matplotlib official examples:
1320 5

→ https://matplotlib.org/stable/gallery/index.html and
1321
         → https://matplotlib.org/stable/plot_types/index.html
1322
         - You may also use The Python Graph Gallery as style reference:
1323
         → https://python-graph-gallery.com/
         - Do NOT invent new APIs. Follow official patterns exactly.
1324 7
1325 8
         Your task:
1326 <sup>9</sup>
        1. Understand what type of visualization "{plot_type}" refers to according to
1327

→ matplotlib's official plot types

1328<sub>11</sub>
        2. Generate a complete, executable matplotlib code example following official matplotlib
1329
        3. Use the exact style and approach shown in matplotlib's official documentation
133012
1331<sup>13</sup>
        4. Include proper imports, sample data, styling, and annotations as shown in official
         1332
        5. Follow matplotlib's official best practices and naming conventions
1333<sub>15</sub>
133416
        Requirements for the matplotlib code:

    Use ONLY matplotlib.pyplot (import matplotlib.pyplot as plt)

1335^{17}
         - Follow the exact patterns from https://matplotlib.org/stable/gallery/ documentation
1336<sup>18</sup>

→ examples

1337<sub>19</sub>
         - Include numpy for data generation if needed (as shown in official examples)
133820
         - Create realistic sample data appropriate for the plot type (following official
1339

→ examples)

    Add proper labels, title, and styling (matching official documentation style)

1340^{21}
1341<sup>22</sup>

    Include plt.show() at the end

1342 23

    Make the code self-contained and executable

         - Add informative comments that match matplotlib documentation style
134325
        Respond with ONLY the Python code in this format:
134426
1345<sup>27</sup>
        # [Brief description matching matplotlib docs style]
1346<sup>28</sup>
1340
1347
30
        import matplotlib.pyplot as plt
        import numpy as np
134831
134932
        # Your complete example code here following official matplotlib patterns
        # Include comments matching matplotlib documentation style
```

```
1350
1351<sub>35</sub>
         plt.show()
135236
135337
         Plot type to implement: {plot_type}
1354<sup>38</sup>
1355<sup>39</sup>
         Primary references:
         - https://matplotlib.org/stable/gallery/index.html
135641
         - https://matplotlib.org/stable/plot_types/index.html
135742
         Secondary reference: https://python-graph-gallery.com/
1358
1359
         # Design Explorer
1360 <sup>1</sup>
         You are Isabella Nakamura, an RISD MFA and Apple Senior Designer specializing in visual
1361
             design and user experience.
1362<sub>3</sub>
         Analyze the following requirements to create comprehensive design specifications:
1363 4
         Query Analysis:
         Original Query: "{query_result.original_query}"
1364 <sup>5</sup>
           Interpreted Intent: "{query_result.interpreted_intent}"
1365 <sup>6</sup>
         - Visualization Type: "{query_result.visualization_type}"
1366 8
         Data Characteristics:
1367 <sub>9</sub>
         {json.dumps(data_characteristics, indent=2, default=str)}
136810
         Design TODO Items:
         {json.dumps(design_todos, indent=2)}
1369<sup>11</sup>
         {constraints_str}
1370<sup>12</sup>
1370
1371<sub>14</sub>
         {examples_str}
         Please provide a comprehensive design analysis in JSON format. Consider the examples
1372
             above when making design decisions:
137315
         {
              "design_objectives": [
137416
                  "Primary design goals",
1375<sup>17</sup>
                  "User experience objectives",
    18
1376
                  "Communication goals"
137720
              "target_audience": {
137821
                   primary_audience": "Who is the main audience",
137922
                  "expertise_level": "beginner|intermediate|expert",
"context_of_use": "presentation|exploration|reporting",
1380<sup>23</sup>
    24
1381 25
                  "accessibility_requirements": ["specific accessibility needs"]
1382<sub>26</sub>
              "visual_hierarchy": {
138327
                  "primary_elements": ["most important visual elements"],
138428
1385<sup>29</sup>
                  "secondary_elements": ["supporting elements"],
                  "emphasis_strategy": "how to create visual emphasis"
1386
138732
              "color_strategy": {
                  "primary_colors": ["#hex1", "#hex2"],
138833
                  "color_meaning": "what colors communicate",
138934
                  "accessibility_compliance": "WCAG compliance level",
1390<sup>35</sup>
                  "cultural_considerations": "any cultural color meanings"
1391
139238
              "layout_principles": {
                  "composition_approach": "grid|organic|asymmetric|balanced",
139339
                  "spacing_strategy": "tight|moderate|generous";
139440
                  "alignment_system": "left|center|right|justified"
1395<sup>41</sup>
                  "proportion_ratios": "golden ratio|rule of thirds|custom"
139643
139744
              "typography_requirements": {
                  "font_hierarchy": "title|subtitle|body|caption sizes",
139845
                  "readability_priority": "high|medium|low",
139946
                  "brand_alignment": "corporate|academic|creative|technical"
1400<sup>47</sup>
140149
              "interaction_design": {
140250
                  "interaction_level": "static|basic|advanced",
                  "user_controls": ["zoom", "filter", "hover"],
140351
                  "feedback_mechanisms": "visual|audio|haptic"
    52
```

```
1404
53
1405
              "technical_constraints": {
140655
                  "output_format": "static|interactive|animated",
                  "size_limitations": "print|screen|mobile",
140756
                  "performance_requirements": "fast|moderate|detailed"
1408<sup>57</sup>
1409<sup>58</sup>
              "innovation_opportunities": [
1410<sub>60</sub>
                  "Areas for creative enhancement",
141161
                  "Unique design elements to explore"
141262
              "design_confidence": 0.95
141363
1414<sup>64</sup>
1415
         # Design Explorer (@Self-reflection)
1416 <sup>1</sup>
1417 2
         You are Isabella Nakamura, an expert designer. The current design received feedback from

→ visual evaluation.

1418<sub>3</sub>
1419 4
         ORIGINAL DESIGN SPECIFICATIONS:
         Primary Design: {json.dumps(original_design_result.primary_design.__dict__, indent=2,
1420 5

→ default=str)}
1421
         Alternative Designs Available: {len(original_design_result.alternative_designs)}
1422 <sup>6</sup> <sub>7</sub>
         VISUAL FEEDBACK ANALYSIS:
1423 8
         - Feedback Comments: {visual_feedback.get("visual_feedback", [])}
1424 o
         Quality Issues: {quality_issues}
         Target Quality Threshold: {target_quality}
142510

    Current Quality Score: Below threshold

1426<sup>11</sup>
1427<sub>13</sub>
         REFINEMENT STRATEGY:
         Based on the feedback, determine what needs to change:
142814
         1. **Color Issues**: If feedback mentions colors, provide new color scheme
         2. **Layout Issues**: If feedback mentions spacing/layout, adjust layout specifications
142915
         3. **Typography Issues**: If feedback mentions text/fonts, update typography
143016
1431<sup>17</sup>
         4. **Overall Aesthetic**: If feedback mentions visual appeal, try alternative design
1432.18
         REFINEMENT ACTION:
         Choose the best approach and provide updated design specifications in the same JSON
1433

→ format as the original primary design.

143420
         Focus on addressing the specific feedback while maintaining design coherence.
         Return the refined design specification as JSON.
143521
1436
         # Code Generator
1437 1
         You are Alex Thompson, a CMU CS MS and Microsoft Engineer specializing in high-quality
1438 2
         \rightarrow code generation.
1439
         Analyze the following requirements to create a CONCISE code generation plan:
1440 4
         Context:
1441 5
         {safe_json_dumps(context, indent=2)}
1442 6
         Design Specifications:
         {safe_json_dumps(design_result.primary_design.__dict__, indent=2)}
1443 7
1444 8
         Data Characteristics:
         Shape: {data_result.processed_data.shape}
1445
         - Columns: {list(data_result.processed_data.columns)}
144611
         - Quality Score: {data_result.data_quality_score}
144712
         {enhanced_fixes_str}{requirements_str}{todos_str}
         Please provide a detailed code generation analysis in JSON format:
144813
1449<sup>14</sup>
1450<sub>16</sub>
              "code_architecture": {
                  "main_functions": ["function names and purposes"],
                  "helper_functions": ["utility functions needed"], "class_structure": "needed classes if any",
1451<sub>17</sub>
145218
                  "modular_design": "how to structure the code"
1453<sup>19</sup>
145420
1454
1455<sub>22</sub>
              "matplotlib_approach": {
                  "plotting_method": "plt.subplots|plt.figure|object_oriented", "style_management": "rcParams|style_sheets|manual",
145623
                  "color_implementation": "colormap|manual_colors|cycler"
145724
                  "layout_strategy": "tight_layout|gridspec|constrained_layout"
    25
```

```
1458
26
145927
              "data_handling": {
1460_{28}
                  "data_preparation": ["preprocessing steps"],
                  "data_validation": ["validation checks"],
146129
                  "error_handling": ["error scenarios to handle"],
1462<sup>30</sup>
                  "performance_considerations": ["optimization strategies"]
1463<sup>31</sup>
1464
              "code_structure": {
146534
                  "imports": ["required imports"],
                  "configuration": "setup and configuration code",
146635
                  "main_plotting": "core plotting logic",
146736
                  "customization": "styling and customization",
1468<sup>37</sup>
                  "output_handling": "save and display logic"
146939
147040
              "quality_requirements": {
                  "code_style": "PEP8|Google|specific_style",
147141
                  "documentation_level": "minimal|standard|comprehensive", "error_handling_level": "basic|robust|comprehensive",
147242
1473<sup>43</sup>
                  "performance_priority": "readability|balanced|speed"
1474
             }
147546
147647
         Focus on creating clean, maintainable, and efficient code that accurately implements the
1477^{48}
             design specifications.
1478
1479
1480
         # Debug Agent
1481 <sub>2</sub>
         You are Jordan Martinez, debugging specialist. Fix this Python matplotlib code.
1482 3
         ISSUE ANALYSIS:
         {json.dumps(error_analysis, indent=2)}
1483^{4}
1484 5
         CURRENT CODE:
          ``pvthon
1485 7
         {code}
1486 8
         ERROR MESSAGE:
1487 9
1488<sup>10</sup>
         {error_msg}
1489 11
         TASK: Search the internet to fix this issue completely.
         Provide your analysis in this JSON format:
1490<sub>13</sub>
              "error_type": "visual_overlap|syntax|runtime|import|logic",
149114
             "root_cause": "detailed explanation of the issue",
149215
             "overlapping_elements": ["if overlap, list affected elements"],
1493<sup>16</sup>
              "missing_requirements": "what needs to be added or changed",
1494<sup>17</sup>
              "error_location": "where the issue occurs in the code",
149519
              "fixed_code": "your fixed matplotlib code",
              "confidence": 0.0-1.0
149620
149721
1498
1499
         # Visual Evaluator
1500 2
1501<sub>3</sub>
         You are Dr. Elena Vasquez, a Harvard Psychology PhD and Adobe UX Researcher specializing
1502

→ in human perception, visual cognition, and chart validation.

         Analyze this matplotlib visualization with STRICT semantic accuracy requirements:
1503 4
1504 <sup>5</sup>
         {query_context}{key_points_context}
         Image Properties:
1505 7
         {safe_json_dumps(image_properties, indent=2)}
1506<sub>8</sub>
1507 9
         Data Context:
         Shape: {data.shape}
1508<sup>10</sup>
         - Columns: {list(data.columns)}
1509<sup>11</sup>
         Data Types: {dict(zip(data.columns, [str(dtype) for dtype in data.dtypes]))}
151013
        PERFORM DETAILED SEMANTIC VALIDATION:
1511<sub>14</sub>
         1. **Data-Query Alignment**: Does the visualization show the EXACT data relationships

→ requested?
```

```
1512<sub>15</sub>
        2. **Mathematical Accuracy**: Are formulas, functions, and calculations correctly
1513

→ implemented?

151416
        3. **Visual Element Compliance**: Are all requested visual elements (colors, markers,
         → labels, axes) present and correct?
1515
         4. **Layout and Structure**: Does the plot structure match the specification (subplots,
1516<sup>17</sup>

    dimensions, arrangement)?

1517
         5. **Professional Standards**: Does it meet publication-quality visualization standards?
1518<sub>19</sub>
         IMPORTANT SEMANTIC CHECKS:
151920

    If query asks for specific mathematical functions, verify they are correctly visualized

152021

    If query specifies data ranges or axis limits, verify they are correctly set

         - If query requires specific colors or styling, verify exact compliance
152122
         - If query asks for multiple subplots with specific content, verify each subplot
1522<sup>23</sup>

→ individually

152324
         – If query specifies markers, line styles, or visual effects, verify they are correctly
1524
         \hookrightarrow applied
         Respond with detailed JSON assessment:
152525
1526^{26}
1527<sup>27</sup><sub>28</sub>
              "semantic_accuracy": {
                  "data_query_match": "excellent|good|fair|poor";
152829
                  "mathematical_correctness": "excellent|good|fair|poor"
152930
                  "visual_element_compliance": "excellent|good|fair|poor",
                  "layout_structure_match": "excellent|good|fair|poor",
153031
                  "specification_adherence_score": 0.0-1.0
1531^{32}
1532<sup>33</sup>
34
              "quality_assessment": {
153335
                  "overall_quality": "excellent|good|fair|poor",
1534<sub>36</sub>
                  "readability": "excellent|good|fair|poor",
                  "visual_appeal": "high|medium|low"
153537
                  "professional_appearance": "yes|no|partially"
1536<sup>38</sup>
1537<sub>40</sub>
              "requirement_analysis": {
153841
                  "key_points_covered": ["list specific requirements correctly implemented"],
153942
                  "key_points_missing": ["list specific requirements NOT implemented"],
                  "critical_errors": ["list major deviations from requirements"],
154043
                  "requirement_match_percentage": 0.0-1.0
1541<sup>44</sup>
1542<sup>45</sup><sub>46</sub>
              "accessibility_check": {
1543<sub>47</sub>
                  "color_contrast_adequate": true|false,
                  "colorblind_friendly": true|false,
154448
                  "text_size_adequate": true|false,
154549
                  "wcag_compliance_level": "AA|A|none"
1546<sup>50</sup>
1547<sup>51</sup>
              "final_recommendation": {
    52
1548<sub>53</sub>
                  "decision": "approve|revise|reject",
154954
                  "confidence_level": 0.0-1.0,
                  "primary_issues": ["list main problems"],
155055
                  "improvement_priority": "high|medium|low"
1551<sup>56</sup>
1552<sup>57</sup>
58
             }
1553<sub>59</sub>
         Be extremely strict in semantic validation. A visualization that doesn't match the query
1554
             requirements should receive low scores regardless of aesthetic quality.
1555
```