

LAMBDA: A Large Model Based Data Agent

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Abstract

We introduce LArge Model Based Data Agent (LAMBDA), a novel open-source, code-free multi-agent data analysis system that leverages the power of large language models. LAMBDA is designed to address data analysis challenges in data-driven applications through innovatively designed data agents using natural language. At the core of LAMBDA are two key agent roles: the programmer and the inspector, which are engineered to work together seamlessly. Specifically, the programmer generates code based on the user's instructions and domain-specific knowledge, while the inspector debugs the code when necessary. To ensure robustness and handle adverse scenarios, LAMBDA features a user interface that allows direct user intervention. Moreover, LAMBDA can flexibly integrate external models and algorithms through our proposed Knowledge Integration Mechanism, catering to the needs of customized data analysis. LAMBDA has demonstrated strong performance on various data analysis tasks. It has the potential to enhance data analysis paradigms by seamlessly integrating human and artificial intelligence, making it more accessible, effective, and efficient for users from diverse backgrounds. The strong performance of LAMBDA in solving data analysis problems is demonstrated using real-world data examples. The code for LAMBDA is available at <https://github.com/AMA-CMFAI/LAMBDA> and videos of three case studies can be viewed at <https://www.polyu.edu.hk/ama/cmfaai/lambda.html>.

Keywords: Code generation via natural language; Data analysis; Large models; Multi-agent collaboration; Software system.

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1 Introduction

Over the past decade, the data-driven approach utilizing deep neural networks has driven the success of artificial intelligence across many challenging applications in various fields (LeCun et al., 2015). Despite these advancements, the current paradigm encounters challenges and limitations in statistical and data science applications, particularly in domains such as biology (Weissgerber et al., 2016), healthcare (Oakes et al., 2024), and business (Weihs and Ickstadt, 2018), which require extensive expertise and advanced coding knowledge for data analysis. A significant barrier is the lack of effective communication channels between domain experts and sophisticated AI models (Park et al., 2021). To address this issue, we introduce a Large Model Based Data Agent (LAMBDA), which is a new open-source, code-free multi-agent data analysis system designed to overcome this dilemma. LAMBDA aims to create a much-needed medium, fostering seamless interaction between domain knowledge and the capabilities of AI in statistics and data science.

Our main objectives in developing LAMBDA are as follows.

(a) Crossing coding barrier: Coding has long been recognized as a significant barrier for domain experts without a background in statistics or computer science, preventing them from effectively leveraging powerful AI tools for data analysis (Oakes et al., 2024). LAMBDA addresses this challenge by enabling users to interact with data agents through natural language instructions, thereby offering a coding-free experience. This approach significantly lowers the barriers to entry for tasks in data science, such as data analysis and data mining, while simultaneously enhancing efficiency and making these tasks more accessible to professionals across various disciplines.

(b) Integrating human intelligence and AI: The existing paradigm of data analysis is confronted with a challenge due to the lack of an efficient intermediary that connects human intelligence with artificial intelligence (Park et al., 2021). On one hand, AI models often lack an understanding of the unlearned domain knowledge required for specific tasks. On the other hand, domain experts find it challenging to integrate their expertise into AI models to enhance their performance (Dash et al., 2022). LAMBDA provides a possible solution to alleviate this problem. With a well-designed interface in our key-value (KV)

knowledge base, the agents can access external resources like algorithms or models. This integration ensures that domain-specific knowledge is effectively incorporated, meets the need for customized data analysis, and enhances the agent’s ability to perform complex tasks with higher accuracy and relevance.

(c) Reshaping data science education: LAMBDA has the potential to become an interactive platform that can transform statistical and data science education. It offers educators the flexibility to tailor their teaching plans and seamlessly integrate the latest research findings. This adaptability makes LAMBDA an invaluable tool for educators seeking to provide cutting-edge, personalized learning experiences. Such an approach stands in contrast to the direct application of models like GPT-4 (OpenAI, 2023; Tu et al., 2024), offering a unique and innovative educational platform.

Beyond these features, the design of LAMBDA also emphasizes reliability and portability. Reliability refers to LAMBDA’s ability to handle data analysis tasks stably and automatically address failures. Portability ensures that LAMBDA is compatible with various large language models (LLMs), allowing it to be continuously enhanced by the latest state-of-the-art models. To save users time on tasks such as document writing, LAMBDA is equipped with the capability for automatic analysis report generation. To accommodate diverse user needs, LAMBDA also supports exporting code to IPython notebook files, such as “ipynb” files in Jupyter Notebook.

While GPT-4 has demonstrated state-of-the-art performance in advanced data analysis, its closed-source nature constrains its adaptability to the rapidly expanding needs of statistical and data science applications and specialized educational fields. Furthermore, concerns regarding data privacy and security risks are inherent in the present configuration of GPT-4 (Bavli et al., 2024). In contrast, by utilizing the open-source LAMBDA, users can alleviate concerns about data privacy by preventing the transmission of user data to external servers. Additionally, it offers greater flexibility and convenience in integrating domain knowledge, installing packages, and utilizing various computational resources.

LAMBDA demonstrates exceptional performance across various datasets used in our system testing. Moreover, it outperforms other data agents in handling complex domain

tasks during our experiments. In summary, our main contributions are as follows: We propose a well-engineered architecture for an LLM-based data agent that enables natural language-driven data analysis in a conversational manner. Unlike typical end-to-end data agents, our design allows human intervention throughout the process, ensuring adaptability when the agent fails to complete a task or misinterprets user intent. Moreover, we introduce a Knowledge Integration mechanism to effectively handle tasks requiring domain-specific knowledge, providing greater flexibility when misalignment occurs in the knowledge. Its ongoing development has the potential to enhance statistics and data science, making advanced tools more accessible to diverse users.

This paper begins with the background and related works in Section 2. Section 3 provides a detailed description of the proposed LAMBDA method. To evaluate its effectiveness, we present our experiments and results in Section 4. Section 5 demonstrates examples and cases of LAMBDA’s application in various scenarios, including data analysis, integration of human intelligence, and interactive education. The paper concludes with a summary in Section 6. More information and details, including implementation, some discussions, datasets, case studies, and experimental settings, are provided in the Supplementary Materials.

2 Background and related works

In recent years, the rapid progress in LLMs like GPT-3, GPT-4, PaLM, LLaMA, and Qwen (Brown et al., 2020; OpenAI, 2023; Chowdhery et al., 2022; Touvron et al., 2023; Bai et al., 2023) has brought boundless possibilities to the field of artificial intelligence and its applications in many fields, including statistics and data science. Benefiting from this revolution, LLM-powered agents (LLM agents) are developed to automatically solve problems in various domains like the search engine, software engineering, gaming, and data science (Guo et al., 2024; Hong et al., 2023; Wu et al., 2023; Zhou et al., 2023; Hong et al., 2023).

2.1 LLMs as data analysis agents

LLM-based data science agent, or data agent, is dedicated to harnessing the power of LLMs to automate data science and analysis tasks (Sun et al., 2024). For example, GPT-4-Advanced Data Analysis and ChatGLM-Data Analysis can analyze user’s data files, perform computations, and generate visualizations (OpenAI, 2023). Some works integrate LLMs into Jupyter Notebooks. For instance, MLCopilot (Zhang et al., 2023) and Chapter (Chapyter, 2023), enable users to interact directly with the notebook, greatly enhancing flexibility. However, they cannot automatically fix errors when they occur and require additional magic commands to support natural language input.

Meanwhile, some researchers focus on designing end-to-end data agents to automate the entire pipeline, including data preprocessing and model evaluation, without human intervention. For example, Data Interpreter (Hong et al., 2024) and TaskWeaver (Qiao et al., 2023) accomplish their tasks through planning and iterative steps. However, current state-of-the-art LLM/VLM-based agents do not reliably automate complete data science workflows (Cao et al., 2024). While fully relying on LLMs for each step reduces human effort, it also significantly increases instability and uncertainty. In addition, if any intermediate step does not align with the user’s intent, the process must be repeated, potentially leading to token waste. In contrast, LAMBDA is designed to support a human-agent collaboration mode, allowing for human intervention at any stage of the process if necessary.

Furthermore, these works have not adequately addressed the high degree of user flexibility needed in data analysis, such as the integration of custom algorithms or statistical models according to user preferences. This flexibility is crucial for enhancing data analysis tasks in domain-specific applications and in statistical and data science education. To address this gap, we have designed a Knowledge Integration Mechanism that allows for the easy incorporation of user resources into our agent system.

2.2 Multi-agent collaboration

A multi-agent system consists of numerous autonomous agents that collaboratively engage in planning, discussions, and decision-making, mirroring the cooperative nature of human

group work in problem-solving tasks (Guo et al., 2024). Each agent has unique capabilities, objectives, and perceptions, operating either independently or collectively to tackle complex tasks or resolve problems (Huang et al., 2023a). Hong et al. (2023) proposed MetaGPT, modeled after a software company, consisting of agents such as Product Manager, Architect, Project Manager, Engineer, and QA Engineer, efficiently breaking down complex tasks into subtasks involving many agents working together. However, even for simple tasks like data visualization, MetaGPT consume a large number of tokens and require more time. In addition, they generate engineering files that need manual execution and lack the immediacy and interactivity essential for intuitive data analysis. In contrast, LAMBDA simplifies the collaboration process by involving only two agents to simulates data analysis workflows, programmer and inspector respectively, reducing token and time consumption. Moreover, its well-designed user interface allows users to intuitively view the analysis results directly on the screen. A comparison and discussion can be found in the supplement materials.

2.3 Knowledge integration

Addressing tasks that require domain-specific knowledge presents a significant challenge for AI agents (Zhang et al., 2024). Incorporating knowledge into LLMs through in-context learning (ICL) is a promising strategy for acquiring new information. A well-known technique in this regard is retrieval-augmented generation (RAG) (Gao et al., 2023), which enhances the accuracy and reduces hallucinations of LLM answers by retrieving external sources (Lewis et al., 2020; Huang et al., 2023b; Borgeaud et al., 2022; Mialon et al., 2023). In RAG, resources are divided into sub-fragments, embedded into vectors, and stored in a vector database. The model first queries this database, identifying document fragments relevant to the user’s query based on the similarity. These fragments are then utilized to refine the answers generated by the LLMs through ICL (Lewis et al., 2020). However, deploying a general RAG approach in data analysis introduces specific challenges. First, the user’s instructions may not align closely with the relevant code fragments in the representation space, resulting in inaccurate searches. Second, when dealing with extensive code, the agents might struggle to contextualize the correct code segments, where accuracy and completeness

are essential for codes and final results.

In addition, custom APIs (Hong et al., 2024) can be implemented to handle domain-specific tasks (Qiao et al., 2023; Hong et al., 2024). For example, systems like Data Interpreter and TaskWeaver invoke the corresponding Tools/Plugins directly within the generated code. Compared to direct parameter-passing, this approach offers greater flexibility in tool usage. However, since the agent cannot access the implementation details of these plugins, it is limited to simple plugin usage and may struggle to resolve misalignment between tools and human instructions when plugin usage is inappropriate.

To address these challenges, we develop a specially designed KV knowledge base with integration methods. This allows users to choose between different modes, including ‘Full’ and ‘Core’, based on the complexity, length of the knowledge context, and specific task requirements. By integrating knowledge, our agent system becomes more adaptable to domain-specific tasks, leveraging human expertise more effectively.

3 Methodology

Our proposed multi-agent data analysis system, LAMBDA, consists of two agents that cooperate seamlessly to solve data analysis tasks using natural language, as shown in Figure 1. The macro workflow describes the code generation process based on user instructions and subsequently executing that code.

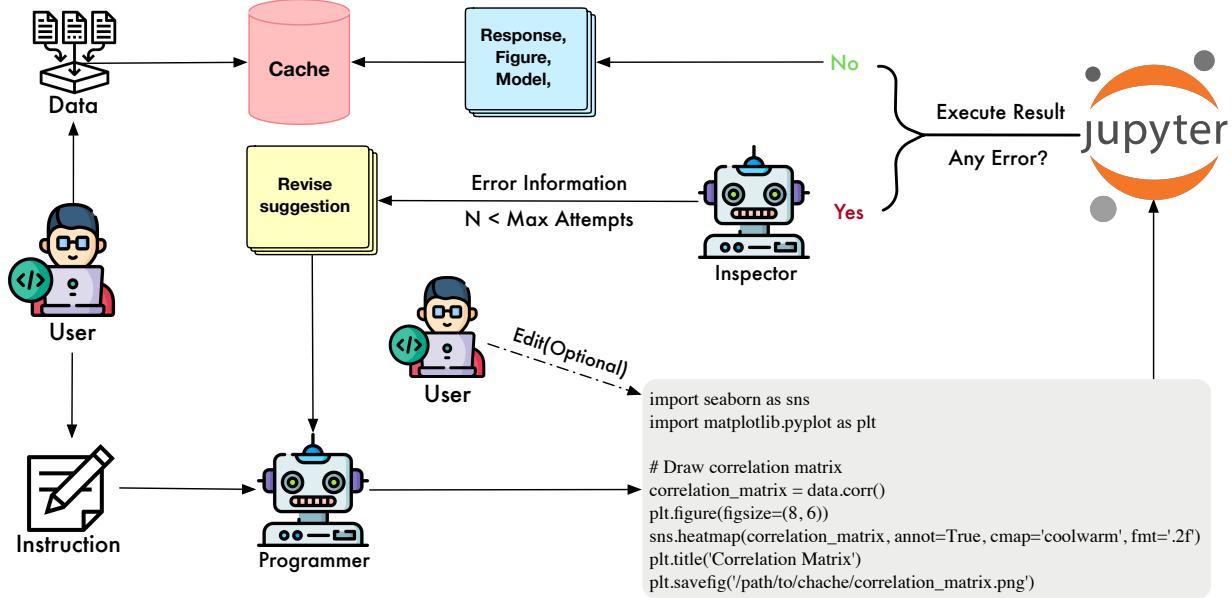


Figure 1: Overview of LAMBDA. LAMBDA features two core agents: the “programmer” for code generation and the “inspector” for error evaluation. The programmer writes and executes code based on user instructions, while the inspector suggests refinements if errors occur. This iterative process continues until the code is error-free or a maximum number of attempts is reached. A human intervention mechanism allows users to modify and run the code directly when needed.

3.1 Overview

LAMBDA is structured around two core agent roles: the “programmer” and the “inspector,” who are tasked with code generation and error evaluation, respectively. The two agents can be implemented separately using either the same or different LLMs. When users submit an instruction, the programmer agent writes code based on the provided instruction and dataset. This code is then executed within the kernel of the host system. Should any errors arise during execution, the inspector intervenes, offering suggestions for code refinement. The programmer takes these suggestions into account, revises the code, and resubmits it for re-evaluation. This iterative cycle continues until the code runs error-free or a preset maximum number of attempts is reached. In order to cope with adverse situations and enhance its reliability and flexibility, a human intervention mechanism is integrated into the workflow. This feature allows users to modify and run the code directly and intervene

when necessary. The multi-agent collaboration algorithm is demonstrated in Algorithm 1.

Algorithm 1 Multi-agent Collaboration. A_n, C_n are the answer and extracted code by the programmer agent in iteration n . We assume each A_n contains C_n , otherwise, the programmer's reply will be returned to the user directly. r is the execution result, E indicates an error, S_n are suggestions provided by the inspector in iteration n , C_h is the code written by a human. The final response is denoted as R .

```

Require:  $Pr$ : Programmer agent
Require:  $I$ : Inspector agent
Require:  $d$ : Dataset provided by user
Require:  $ins$ : Instructions provided by user
Require:  $T$ : Maximum number of attempts

1:  $n \leftarrow 0$                                  $\triangleright$  Initialize iteration counter
2:  $C_n \leftarrow A_n, A_n \leftarrow Pr(d, ins)$      $\triangleright$  Extract code and answer by Programmer
3:  $r = \begin{cases} r, & \text{success} \\ E, & \text{error} \end{cases} \leftarrow execute(C_n)$      $\triangleright$  Code execution, similarly to subsequent  $r$ 
4: while  $r = E$  and  $n < T$  do                 $\triangleright$  Self-correcting mechanism start
5:    $n \leftarrow n + 1$ 
6:    $S_n \leftarrow I(C_{n-1}, E)$                    $\triangleright$  Inspector provides suggestions
7:    $C_n \leftarrow A_n, A_n \leftarrow Pr(C_{n-1}, S_n, E)$      $\triangleright$  Programmer modifies code
8:    $r \leftarrow execute(C_n)$                        $\triangleright$  Execute modified code
9: end while
10: if  $r = E$  then
11:    $r \leftarrow execute(C_h)$                      $\triangleright$  Human intervention (Optional)
12:    $R \leftarrow C_h \cup Pr(r)$                    $\triangleright$  Final response in natural language
13: end if
14:  $R \leftarrow C_n \cup Pr(r)$                    $\triangleright$  Final response in natural language

```

3.2 Programmer agent

The main responsibility of the programmer is to write code and respond to the user. Upon the user's dataset upload, the programmer receives a tailored system prompt that outlines the programmer's role, environmental context, and the I/O formats. This prompt is augmented with examples to facilitate few-shot learning for the programmer. Specifically, the system prompt encompasses the user's working directory, the storage path of the dataset, the dimensions of the dataset, the name of each column, the type of each column, information on missing values, and statistical description.

The programmer's workflow can be summarized as follows: initially, the programmer

writes code based on instructions from the user or the inspector; subsequently, the program extracts code blocks from the programmer’s output and executes them in the kernel. Finally, the programmer generates a final response based on the execution results and communicates it to the user. This final response consists of a summary and suggestions for the next steps.

3.3 Inspector agent and self-correcting mechanism

The inspector’s role is to provide modification suggestions when errors occur in code execution. The prompt of the inspector includes the code written by the programmer during the current dialogue round and the error messages from the kernel. The inspector will offer actionable revision suggestions to the programmer for code correction. This suggestion prompt contains the erroneous code, kernel error messages, and the inspector’s suggestions. This collaborative process between the two agents iterates several rounds until the code executes successfully or the maximum number of attempts is reached. This self-correcting mechanism enables the programmer and inspector to make multiple attempts in case of error. A case of self-correcting mechanism and released experiment can be found in the Supplementary Materials.

3.4 Integrating human intelligence and AI

Beyond leveraging the inherent knowledge of LLMs, LAMBDA is further enhanced to integrate human intelligence through external resources such as customized algorithms and statistical models from users. As mentioned above, the challenges faced by general RAG methods in data analysis stem from the potential lack of clear correlation between user instructions and code fragments in the representation space, as well as the impact of the length of code fragments. We design a special KV knowledge base for this challenge.

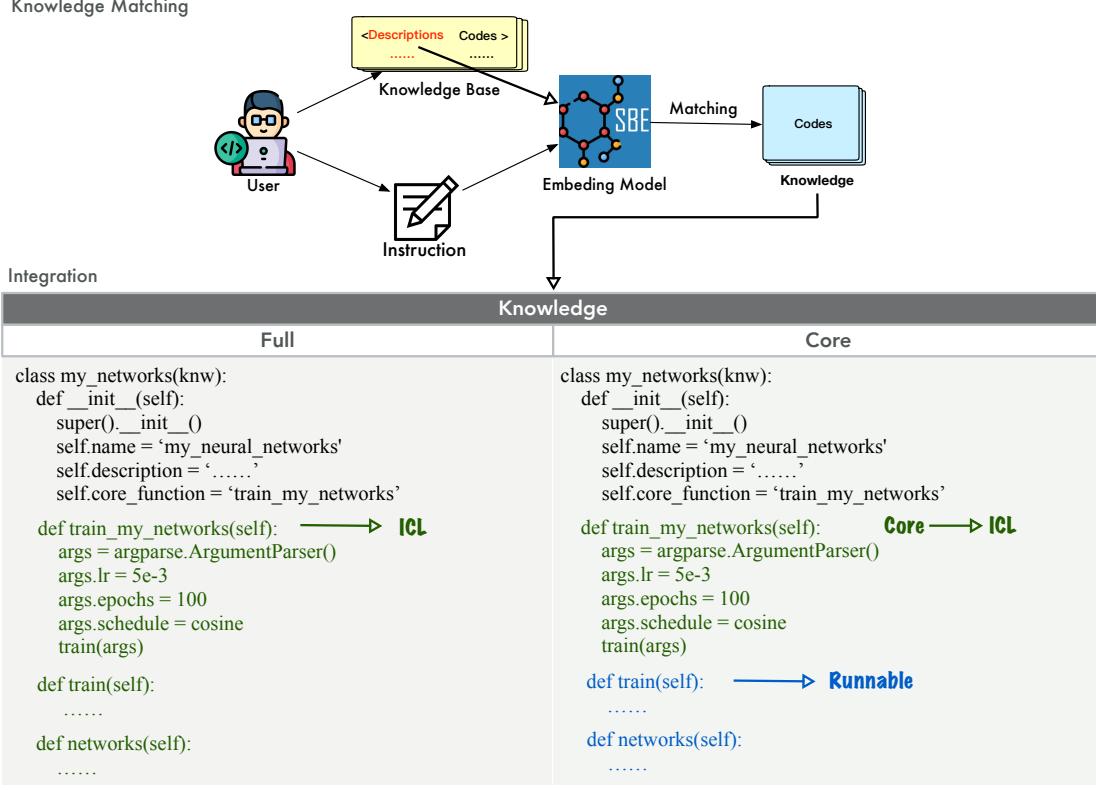


Figure 2: Knowledge Integration Mechanism in LAMBDA: Knowledge Matching selects codes from the knowledge base by comparing descriptions with the instruction. Two integration modes are available: ‘Full’ mode injects the entire knowledge code into the LLM via ICL, while ‘Core’ mode segments the code into essential usage for ICL and runnable code for back-end execution.

The KV knowledge base is a repository for housing external resources from users in key and value pairs. Specifically, we format the code of resources into key-value pairs: the key represents the resource description, and the value denotes the code. The user’s query will be matched within the knowledge base to select the code with the highest similarity. Figure 2 demonstrates the workflow of knowledge matching in LAMBDA. We define the knowledge base as $\mathcal{K} = \{(d_i, c_i) \mid i = 1, 2, \dots, n\}$, where d_i represents the description of the i -th piece of knowledge and c_i represents the corresponding source code.

When the user issues an instruction ins , an embedding model \mathcal{F} encodes all descriptions in the knowledge base and the ins , such as Sentence-BERT (Reimers and Gurevych, 2019). The embedding tensors for descriptions and instruction are represented by \mathbf{e}_{d_i} and \mathbf{e}_{ins}

respectively. The cosine similarity between them is calculated to select knowledge with a similarity score greater than a threshold θ , with the highest-scoring match chosen as the relevant knowledge.

Let the embedding function be \mathcal{F} , the \mathbf{e}_{d_i} and \mathbf{e}_{ins} are formulated as follows $\mathbf{e}_{d_i} = \mathcal{F}(d_i), i \in \{1, 2, \dots, n\}$, and $\mathbf{e}_{ins} = \mathcal{F}(ins)$. The similarity S_i between description and instruction is computed using cosine similarity as

$$S_i(\mathbf{e}_{d_i}, \mathbf{e}_{ins}) = \frac{\mathbf{e}_{d_i} \cdot \mathbf{e}_{ins}}{\|\mathbf{e}_{d_i}\| \|\mathbf{e}_{ins}\|} \quad \forall i \in \{1, 2, \dots, n\}.$$

The matched knowledge k with the highest S_i is selected while it satisfies $S_i > \theta$, computed as

$$k = c_{i^*}, \quad i^* = \arg \max_i \left(S_i(\mathbf{e}_{d_i}, \mathbf{e}_{ins}) \cdot \mathbf{1}_{\{S_i(\mathbf{e}_{d_i}, \mathbf{e}_{ins}) > \theta\}} \right) \quad \forall i \in \{1, 2, \dots, n\}.$$

The knowledge k will be embedded in ICL for the LLM to generate answer \hat{A} . Formally, given a query q , matched knowledge k , a set of demonstrations $D = \{(q_1, k_1, a_1), (q_2, k_2, a_2), \dots, (q_n, k_n, a_n)\}$, and the LLM \mathcal{M} , the model estimates the probability $\mathcal{P}(a|q, k, D)$ and outputs the answer \hat{A} that maximizes this probability. The final response \hat{A} is generated by the model \mathcal{M} as $\hat{A} \leftarrow \mathcal{M}(q, D)$.

The matching threshold θ defines the required similarity between a knowledge description and a user instruction, directly influencing the complexity of retrieving relevant knowledge. A higher θ imposes stricter matching criteria, reducing the chance of retrieval, whereas a lower θ increases the probability of identifying a match.

The optimal selection of θ depends on multiple factors. For example, when users aim to incorporate specific knowledge into a task, a lower θ value increases the chance of retrieving the relevant information. Furthermore, the length of the knowledge description plays a critical role, as longer descriptions typically necessitate a lower θ value since user instructions are generally more concise. By default, we recommend setting θ to 0.2. However, this value can be adjusted based on the aforementioned factors to optimize retrieval performance.

By integrating k through ICL, the model effectively combines retrieved domain knowledge

with contextual learning to provide answers that are more accurate. Moreover, LAMBDA offers two integration modes: ‘Full’ and ‘Core’. In the ‘Full’ mode, the entire knowledge is utilized as the context in ICL. In the ‘Core’ mode, the core functions are processed through ICL, while other functions are executed directly in the back-end. This approach allows the agents to focus on modifying the core function directly, without the need to understand or implement the sub-functions within it. The ‘Core’ mode is particularly effective for scenarios involving lengthy code, as it eliminates the need to process the entire code through ICL. These two modes of knowledge integration provide substantial flexibility for handling tasks that require domain-specific knowledge. We evaluate our Knowledge Integration Mechanism in Table 8 through several domain tasks.

In summary, the Knowledge Integration Mechanism empowers LAMBDA to perform domain tasks and offers the flexibility needed to address complex data analysis challenges.

3.5 Kernel, report generation and code exporting

LAMBDA uses IPython as its kernel to manage sequential data processing, where each operation builds on the previous one, such as standardization followed by one-hot encoding. Implementation details are in the Supplementary Materials. LAMBDA also generates analysis reports from dialogue history, including data processing steps, visualizations, model descriptions, and evaluation results. Users can choose from various report templates, and the agent creates reports via ICL, allowing users to focus on higher-value tasks. A sample report is in Figure 9 and the Supplementary Materials. Moreover, users can download their experimental code as an IPython notebook.

3.6 User interface

LAMBDA provides an accessible user experience similar to ChatGPT. Users can upload datasets and describe tasks in natural language, supported by LLMs like Qwen-2, which recognizes 27 languages. It is recommended to prompt LAMBDA step-by-step, mimicking data analysts’ approach, to maintain control and embody the “human-in-the-loop” concept. LAMBDA generates results, including code, figures, and models, which users can copy and

save with a single click. Even those without expertise in statistics or data science can train advanced models by simply asking for recommendations, such as XGBoost and AdaBoost. Advanced users can customize LAMBDA’s knowledge via an interface template. Users can also export text reports and code for further study. A usage example is shown in Figure 9. LAMBDA’s interface is designed to be accessible to users of all backgrounds.

To summarize, the programmer agent, inspector agent, self-correcting mechanism, and human-in-the-loop components collectively ensure the reliability of LAMBDA. The integration of knowledge makes LAMBDA scalable and flexible for domain-specific tasks. To enhance portability, we provide an OpenAI-style interface for LAMBDA. This ensures that most LLMs, once deployed via open-source frameworks such as vLLM (Kwon et al., 2023) and LLaMA-Factory (Zheng et al., 2024b), are compatible with LAMBDA.

3.7 Prompt

We present examples of prompts for the roles of programmer, inspector, self-corrector, and knowledge integrator. Additional prompt examples and case studies are available in the Supplementary Materials.

Figure 3 gives an example prompt for the data analyst at the start of the analysis session.

System Prompt for Programmer

You are a data analyst, your mission is to help humans do tasks related to data science and analysis. You are connecting to a computer. You should write Python code to complete the user's instructions. Since the computer will execute your code in Jupyter Notebook, you should directly use defined variables instead of rewriting repeated code. And your code should be started with markdown format like:

```python

**Write your code here.**

```

..... You can work with data uploaded to your computer by users, the working path of the user is **{working_path}**. You must read or save files in this path. \nHere is an example:

{example}

Figure 3: Prompt example for the data analyst.

Figure 4 shows a system prompt about the dataset, which provides essential information to the programmer agent.

System Prompt for Dataset

```
Now, the user uploads the dataset in {working_path}, and here is the general information of the dataset:{  
'num_rows': 150,  
'num_features': 5,  
'features': Index(['Sepal.Length', 'Sepal.Width', 'Petal.Length', 'Petal.Width'],  
                  'Species'],  
                  dtype='object') .....  
'missing_val': Sepal.Length 0\\nSepal.Width 0\\nPetal.Length 0\\nPetal.Width 0\\nSpecies 0\\ndtype: int64,  
'describe': Sepal.Length Sepal.Width Petal.Length Petal.Width  
count 150.00 150.00 150.00 150.00  
mean 5.84 3.06 3.76 1.20 .....}
```

Figure 4: Prompt example for the dataset.

After obtaining the execution results, a prompt such as the one given in Figure 5 can be used to format the output, enabling the programmer agent to provide an explanation or suggest the next steps.

Prompt for Execution Result

This is the execution result by the computer (If nothing is printed, it may be figures or files):
{Executing_result}.
You should use 1-3 sentences to explain or give suggestions for next steps:

Figure 5: Prompt example for the execution result.

When an error occurs, a prompt for the inspector is employed to guide the inspector in identifying the cause of the bug and to offer revision suggestions (Figure 6).

Prompt for Inspector

You are an experienced and insightful inspector, and you need to identify the bugs in the given code based on the error messages and give modification suggestions.
- bug code:
{bug_code}\\n
When executing the above code, errors occurred: {error_message}.
Please check the implementation of the function and provide a method for modification based on the error message. No need to provide the modified code.
Modification method:

Figure 6: Prompt example for inspector.

Figure 7 presents an example prompt for the programmer revising the error code.

Prompt for Programmer to Fix the Bug

You should attempt to fix the bugs in the bellow code based on the provided error information and the method for modification. Please make sure to carefully check every potentially problematic area and make appropriate adjustments and corrections.

If the error is due to missing packages, you can install packages in the environment by “!pip install package_name”.\n

- bug code:

{bug_code}\n

When executing the above code, errors occurred: {error_message}.

Please check and fix the code based on the modification method.\n

- modification method:

{fix_method}\n

The code you modified (should be wrapped in `python`):

Figure 7: Prompt example for code correction.

For knowledge integration, the system message prompt and retrieval result are shown in Figure 8.

Prompt for Knowledge Integration

System Prompt for Retrieval

You can retrieve codes from the knowledge base. The retrieved code will be formatted as:

Retrieval: The retriever finds the following pieces of code cloud address the problem:\n```python\n[retrieval_code]\n```

For example:

{example}

Prompt for Retrieval

Retrieval: The retriever finds the following pieces of code cloud address the problem. You should refer to this code and modify it as appropriate.

Retrieval code:

{code}

Figure 8: Prompt example for knowledge integration.

4 Experiments

4.1 Data experiments

The current data analysis paradigm relies on programming software and languages such as R (R Core Team, 2023), SAS (SAS Institute Inc., 2015), and Python (Python Software Foundation, 2023) for computation and experimentation. To gain practical experience and evaluate LAMBDA’s performance in real-world data science tasks, we first applied LAMBDA to several standard datasets for classification and regression analysis. In addition,

we conducted further investigations in broader statistical analysis scenarios, such as high-dimensional data, missing data, image data, and text data, to examined its robustness and versatility. All information of the datasets used can be found in the supplementary materials.

DataSets	Usage
AIDS Clinical Trials Group Study 175 (Hammer et al., 1996)	Classification
NHANES (Dinh et al., 2023).	Classification
Breast Cancer Wisconsin (Wolberg et al., 1995)	Classification
Wine (Aeberhard and Forina, 1991)	Classification
Concrete Compressive Strength (Yeh, 2007)	Regression
Combined Cycle Power Plant (Tfekci and Kaya, 2014)	Regression
Abalone (Nash et al., 1995)	Regression - Case Study
Airfoil Self-Noise (Brooks et al., 2014)	Regression
Iris (Fisher, 1988)	Classification - Case Study
Heart Disease (Janosi et al., 1988)	Regression - Case Study
Genomic Datasets (Anh, 2023)	High-Dimensional Data
Framingham Heart Study Dataset (FHS, 1948)	Missing Data
Student Admission Records (Kaggle SAD, 2016)	Missing Data
MINIST (LeCun et al., 1998)	Image Data
SMS Spam (Almeida et al., 2011)	Text Data

Table 1: Datasets used in this study. The Genomic datasets include the following three datasets: TCGAmirna (Bentink et al., 2012), EMTAB386 (Colaprico et al., 2015), and GSE49997 (Pils et al., 2012).

For classification problems, we measured accuracy on the test data, defined as the ratio of correctly classified instances to the total number of instances. For regression problems, we used Mean Squared Error (MSE), which is the average of the squared differences between the predicted values and the actual values in the test data. The formula for MSE is: $MSE = (1/n) \sum_{i=1}^n (y_i - \hat{y}_i)^2$, where n is number of data points, y_i is the observed value, \hat{y}_i is the predicted value. We employed 5-fold cross validation for evaluation in all the cases. Table S.5 lists the datasets used in our experiments and case studies.

4.1.1 Experiments with classical tabular data

We initially applied LAMBDA to several classical datasets, covering both classification and regression tasks. To facilitate comparison, we documented the analysis methods employed by LAMBDA and then manually conducted the same analyses using R. The results are summarized in Table 2, with the corresponding results from the R analyses presented in parentheses.

Table 2: The experimental results obtained using LAMBDA and R are presented, with the R results indicated in parentheses. Classification problems were evaluated using accuracy, where higher values indicate better performance. Regression problems were assessed using mean squared error (MSE), where lower values are preferable. All results were derived from 5-fold cross-validation. The difference result bewteen LAMBDA and R is introduced by different data processing, hyper-paprameters and cross-validation.

Model		Datasets			
		AIDS (%)	NHANES (%)	Breast Cancer(%)	Wine(%)
Classification	Logistic Regression	86.54 (86.44)	99.43 (99.96)	98.07 (97.72)	98.89 (98.86)
	SVM	88.45 (88.59)	98.82 (98.86)	97.72 (98.25)	98.89 (98.33)
	Neural Network	88.82 (87.89)	99.91 (99.91)	97.82 (97.01)	82.60 (98.87)
	Decision Tree	87.70 (88.78)	100 (100)	94.26 (93.32)	92.14 (90.91)
	Random Forest	89.29 (88.73)	100 (100)	96.84 (95.96)	98.33 (98.30)
	Bagging	89.62 (88.82)	100 (100)	96.49 (94.90)	96.65 (96.60)
	Gradient Boost	89.20 (88.83)	100 (100)	96.84 (94.74)	96.65 (98.89)
	XGBoost	89.67 (89.62)	100 (100)	97.54 (97.19)	95.54 (98.87)
Regression	AdaBoost	88.92 (89.10)	100 (100)	97.72 (97.55)	93.89 (97.71)
	Best Accuracy	89.67 (89.62)	100 (100)	98.07 (98.25)	98.89 (98.89)
		Concrete	Power Plant	Abalone	Airfoil
Regression	Linear Regression	0.4596 (0.3924)	0.0714 (0.0713)	0.5086 (0.6867)	0.5717 (0.6972)
	Lasso	0.5609 (0.3918)	0.0718 (0.0713)	0.8042 (0.4739)	0.5738 (0.4886)
	SVR	0.4012 (0.4780)	0.0534 (0.0489)	0.4542 (0.4408)	0.3854 (0.3725)
	Neural Network	0.2749 (0.3055)	0.0612 (0.0567)	0.4551 (0.7185)	0.4292 (0.2604)
	Decision Tree	0.5242 (0.5837)	0.0551 (0.1175)	0.5566 (0.5472)	0.3823 (0.2559)
	Random Forest	0.4211 (0.2755)	0.0375 (0.0363)	0.4749 (0.4460)	0.2655 (0.3343)
	Gradient Boost	0.3414 (0.3605)	0.0315 (0.0538)	0.4778 (0.5840)	0.2528 (0.2888)
	XGBoost	0.3221 (0.2991)	0.0319 (0.0375)	0.4778 (0.4441)	0.2741 (0.2832)
	CatBoost	0.2876 (0.4323)	0.0325 (0.0568)	0.4795 (0.4516)	0.2529 (0.2638)
	Best MSE	0.2749 (0.2755)	0.0315 (0.0363)	(0.4542) 0.4408	0.2528 (0.2559)

The results presented in Table 2 demonstrate LAMBDA’s robust performance in executing data analysis tasks. These results are either superior to or on par with those obtained using R. These outcomes highlight LAMBDA’s effectiveness in leveraging various models

across tabular data scenarios. Furthermore, the results indicate that LAMBDA performs at a level comparable to that of a data analyst proficient in R. This suggests the potential for systems like LAMBDA to become indispensable tools for data analysis in the future. Notably, there was no human involvement in the entire experimental process with LAMBDA, as only prompts in English were provided.

In summary, the experimental results demonstrate that LAMBDA achieves human-level performance and can serve as an efficient and reliable data agent, assisting individuals in handling data analysis tasks.

4.1.2 Experiments with high-dimensional data and unstructured data

To validate LAMBDA’s robustness and versatility, we further explored its application across a broader range of data scenarios, including high-dimensional data, missing data, image data, and text data.

- **High-dimensional data:** We evaluated LAMBDA on the following three challenging high-dimensional clinical datasets: TCGAmirna (Bentink et al., 2012), EMTAB386 (Colaprico et al., 2015), and GSE49997 (Pils et al., 2012). We summarize the sample size and dimensions in Table 3. The test results are presented in Table 4. More detailed descriptions of these three datasets are given in the Supplementary Materials. We found that LAMBDA consistently applies dimensionality reduction techniques, such as Principal Component Analysis (PCA), as a preprocessing step. This allows us to apply methods like logistic regression without the regularization. The results indicate that LAMBDA is capable of handling high-dimensional data.

Data	TCGAmirna	EMTAB386	GSE49997
(Size, Dimension)	(544, 802)	(129, 10360)	(194, 16051)

Table 3: Experiment datasets with their sizes and dimensions (rows, columns).

- **Missing data:** We evaluated LAMBDA on three datasets containing missing values, with results summarized in Table 5. We observe that LAMBDA tends to prioritize deleting the observations that contain missing values. However, with an appropriate

Model	TCGAmirna (%)	EMTAB386 (%)	GSE49997 (%)
Logistic Regression	52.58	54.18	67.52
Decision Tree	54.42	57.45	63.45
Random Forest	55.16	61.20	67.54
Bagging	56.62	58.21	70.63
Gradient Boosting	54.78	55.08	70.62
XGBoost	55.15	58.15	70.62
AdaBoost	55.15	57.45	70.62
Neural Network	54.22	61.23	66.48
Best	56.62	61.23	70.63

Table 4: Performance on the high-dimensional datasets. The results are reported in terms of accuracy through 5-fold cross-validation.

prompt, LAMBDA can also attempt to impute missing values (e.g., mean value). When errors arise due to missing values, the Inspector agent effectively identifies the issue, notifies the Programmer agent, and applies the necessary corrections.

Model	Framingham (%)	StuRecord (%)	Heart Disease (%)
Logistic Regression	85.35	50.36	59.41
Neural Network	84.95	57.28	60.40
Decision Tree	84.27	52.96	52.49
Random Forest	85.19	55.40	60.39
Bagging	85.02	58.65	60.06
Gradient Boosting	85.12	60.50	58.41
XGBoost	85.19	61.05	60.71
AdaBoost	84.98	56.63	59.42
Best	85.35	61.05	60.40

Table 5: Performance on Framingham, StuRecord and Heart Disease datasets. The results are reported in terms of accuracy through 5-fold cross-validation.

- **Image data:** We used LAMBDA to train a handwritten digit classifier based on the MNIST dataset. We prompted LAMBDA to utilize various neural network architectures, such as Convolutional Neural Networks (CNNs) and Transformers, as backbone models. The results of this experiment are presented in Table 6. According

to Table 6, we find LAMBDA can effectively implement and apply deep learning architectures like CNNs and Transformers for image classification tasks.

Model	Accuracy (%)
CNN	99.19
Transformer	97.23

Table 6: Performance on the MNIST Dataset.

- **Text data:** We used LAMBDA to train a spam detection classifier based on the SMS Spam Collection Dataset. Similar to our approach with image data, we prompted LAMBDA to experiment with different backbone models for this task. The results are summarized in Table 7. As shown in Table 7, LAMBDA successfully performed text classification tasks. Notably, when prompted to use a Transformer-based architecture, LAMBDA employed DistilBERT-Base-Uncased for transfer learning, which significantly improved both training efficiency and model performance.

Model	Accuracy (%)
Multinomial Naive Bayes	98.39
BERT	99.37

Table 7: Performance of different backbones on the SPAM classification task.

Overall, our findings indicate that LAMBDA is not only capable of handling tabular tabular tasks but also effectively processing image and text data. In future work, we aim to explore more complex and diverse data scenarios.

4.2 Performance of Knowledge Integration

We collected three domain-specific tasks to evaluate the proposed Knowledge Integration Mechanism and compare it with advanced data analysis agents. Specifically, the tasks involve utilizing the recent algorithm packages (e.g., PAMI (Piotrowski et al., 2021)), implementing optimization algorithms (e.g., computing the nearest correlation matrix), and training the

latest research models (e.g., non-negative neural networks). For each task, we define a score S that is calculated as follows:

$$S = \begin{cases} 0, & \text{code error and execution error, or exceeded runtime limit,} \\ 0.5, & \text{code error and execution successful,} \\ 0.8, & \text{code successful, execution error due to other issues, e.g. environment,} \\ 1, & \text{both code and execution successful.} \end{cases}$$

To ensure maximum alignment in experimental settings, we converted the code into corresponding tools for agents equipped with a tools mechanism. For agents lacking such a mechanism, we directly included the code in their context. All agents are implemented using GPT-3.5, except for methods and platforms that have their own models, such as GPT-4-Advanced Data Analysis, ChatGLM-Data Analysis, and OpenCodeInterpreter. Since each task can be completed within one minute, we set a maximum runtime limit of 5 minutes to prevent some agents from becoming stuck in infinite self-modification loops.

- *Pattern Mining* Piotrowski et al. (2021) introduce PAMI (PAttern MIning), a cross-platform, open-source Python library offering algorithms to uncover patterns in diverse databases across multiple computing architectures.
- *Nearest Correlation Matrix* Qi and Sun (2006) propose a Newton-type method specifically designed for the nearest correlation matrix problem. Numerical experiments validate the method’s fast convergence and high efficiency.
- *Fixed Points Non-negative Neural Networks* Rage et al. (2024) analyze nonnegative neural networks, which are defined as neural networks that map nonnegative vectors to nonnegative vectors.

Table 8 demonstrates the effectiveness of LAMBDA’s Knowledge Integration mechanism. Specifically, our results showed that many methods scored zero, particularly when the code was lengthy or involved unfamiliar packages not encountered during LLM training. In these

	PM	NCM	FPNENN
GPT-4-Advanced Data Analysis (OpenAI, 2023)	0.80 (4)	0 (1)	0 (1)
ChatGLM-Data Analysis (Du et al., 2022)	0 (2)	0 (2)	0 (2)
OpenInterpreter (Interpreter, 2023)	0 (2)	0 (2)	0 (2)
OpenCodeInterpreter (Zheng et al., 2024a)	1.00 (5)	0 (1)	0 (1)
Chapyter (Chapyter, 2023)	0 (2)	0 (2)	0 (2)
DataInterpreter (Tools) (Hong et al., 2024)	1.00 (5)	1.00 (5)	1.00 (5)
TaskWeaver (Plugins) (Qiao et al., 2023)	1.00 (5)	1.00 (5)	1.00 (5)
LAMBDA (Knowledge)	1.00 (5)	1.00 (5)	1.00 (5)

Table 8: Performance of the Knowledge Integration Mechanism. In the table, ‘PM’ refers to pattern mining, ‘NCM’ refers to the nearest correlation matrix, and ‘FPNENN’ stands for fixed points in non-negative neural networks. The values represent the performance scores, with failure reasons noted in brackets. Specifically, 1: code error and execution error; 2: exceeded runtime limit; 3: code error but successful execution; 4: right code but execution error due to other issues; 5: right code and successful execution.

situations, most other approaches struggle with one-shot learning. Two exceptions are Data Interpreter and TaskWeaver, which successfully complete the task using pre-defined Plugins/Tools. With the pre-defined Plugins/Tools, they can execute operations internally without requiring the LLM to generate precise code. This mechanism is similar to the ‘Core’ mode of our LAMBDA.

With these tools, the LLM only needs to learn a given code usage example rather than generating the full internal implementation, even when it has access to those details. Although these approaches are generally suitable, the agent is likely to make mistakes when there is the certain misalignment between the users’ instructions and integrated knowledge. In such circumstances, we need to utilize the ‘Full’ mode of our LAMBDA. To further support our claim, we designed two additional experiments.

We take the fixed point non-negative neural networks as a example. We further explore the following two cases that involve misalignment in integrating knowledge/tools and human instruction, which require modifications to the tools (the loss and network mapping are annotated in the schema):

- **Case 1:** The instruction specifies the use of L1 Loss, whereas the tool are originally

configured with MSE Loss.

- **Case 2:** The instruction specifies a network structure mapping as follows:

- Encoder: $784 \rightarrow 400$, whereas $784 \rightarrow 200$ originally configured.
- Decoder: $400 \rightarrow 784$, whereas $200 \rightarrow 784$ originally configured.

Methods	Misalignment Loss	Misalignment Network
TaskWeaver (Plugins)	✗ Directly using the plugin	✗ Directly using the plugin
Data Interpreter (Tools)	✗ Directly use the tool	✗ Directly use the tool
LAMBDA (Knowledge)	✓ Alignment	✓ Alignment

Table 9: The results of case study on Misalignment between Tools and Instructions. Both Plugins and Tools Integration directly use the tools and are not aware of the Misalignment between Tools and Instructions.

From Table 9, we observe that in Cases 1 and 2, which require modifications to the tools, both TaskWeaver and Data Interpreter directly use the original tools without recognizing that the tools no longer meet the new requirements although the loss and network mapping are annotated in the schema. In contrast, due to the visibility of the knowledge code under ‘Full’ mode, LAMBDA identifies that the original code cannot satisfy the new requirements, makes the necessary adjustments, and successfully completes the two cases.

5 Examples

We present an example of using LAMBDA for building a classification model in Figure 9. We also provide three case studies in video format to demonstrate the use of LAMBDA in data analysis, integrating human intelligence and AI, and education.

- *Data Analysis* We simulate scenarios in which the user requests LAMBDA to perform various tasks, including data preprocessing, data visualization, and model training, on the provided Iris dataset (Fisher, 1988). LAMBDA consistently delivers accurate responses. Additionally, LAMBDA generates an analysis report based on the chat history. A demonstration of this process is given in the first video at <https://www.polyu.edu.hk/ama/cmfai/lambda.html>.

- *Integrating Human Intelligence and AI* We demonstrated the Knowledge Integration capabilities of LAMBDA by computing the nearest correlation matrix using the Quadratically Convergent Newton Method. We first highlighted the limitations of GPT-4-Advanced Data Analysis in performing this task, thereby underscoring the value of LAMBDA through comparison. A demonstration is given in the second video at <https://www.polyu.edu.hk/ama/cmfai/lambda.html>.
- *Interactive Education* We consider an educational scenario in which the teacher uses LAMBDA to design the exercise assignments, and the students use LAMBDA to complete exercises. The exercise dataset used is Abalone. This educational support system enhances the efficiency of both teaching and learning. A demonstration is given in the third video at <https://www.polyu.edu.hk/ama/cmfai/lambda.html>.

Figure 9: An example of using LAMBDA for classification analysis with the Wine dataset.

6 Conclusion

LAMBDA is an open-source multi-agent data analysis system that effectively integrates human intelligence with artificial intelligence. Experimental results demonstrate that LAMBDA achieves satisfactory performance in handling various data analysis tasks. In the future, LAMBDA can be further enhanced with advanced planning, reasoning techniques, and knowledge integration methods to address a broader range of domain-specific tasks. Our results and examples underscore the significant potential of LAMBDA to enhance both statistical and data science practice and education.

By bridging the gap between human expertise and AI capabilities, LAMBDA aims to democratize data science and statistical analysis, fostering a more inclusive environment for innovation and discovery. Its open-source nature encourages collaboration and continuous improvement from the global research community, allowing researchers and developers to contribute to its evolution. As LAMBDA continues to develop, it has the potential to become an invaluable tool for statisticians, data scientists, and domain experts, enhancing their ability to analyze data efficiently and effectively.

Moreover, LAMBDA holds significant potential for statistical and data science education. Its natural language interface lowers barriers for educators and students, enabling them to focus on problem formulation rather than getting bogged down by syntactic complexities. By generating executable code for various tasks, LAMBDA provides immediate, actionable feedback, which can enhance the learning experience by allowing students to see the direct impact of their queries and hypotheses. This capability not only aids in teaching fundamental concepts but also empowers students to experiment and explore data-driven insights independently.

Future work on LAMBDA could focus on several key areas. First, enhancing LAMBDA’s ability to seamlessly integrate and leverage large models from various domains for statistical analysis could significantly improve its capacity to tackle complex data analysis tasks. Second, improving the user interface and increasing user satisfaction would make the system more accessible to non-experts. Third, incorporating real-time data processing capabilities could enable LAMBDA to handle streaming data, which is increasingly important in many

applications. Finally, expanding the system’s support for collaborative work among multiple users could further enhance its utility in both educational and professional settings. We plan to implement LAMBDA in our classroom teaching scenarios, continuously gather feedback from various groups, and use user satisfaction as a metric for evaluating LAMBDA.

In conclusion, LAMBDA represents a meaningful step forward in integrating human and artificial intelligence for data analysis. Its continued development and refinement have the potential to advance the fields of statistics and data science, making sophisticated analytical tools more accessible to users from diverse backgrounds. We have made our code available at <https://github.com/AMA-CMFAI/LAMBDA>.

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Supplementary Materials

The Supplementary Materials provide key methodological details, experimental data, case studies, and the experimental setup. Specifically, Section A introduces our initial concept of a function-calling-based agent system along with relevant discussions. Section B details the core modules involved in kernel development and describes the datasets used in our experiments. Section C elaborates on the implementation of the Knowledge Base and Knowledge Integration. In Section D, we analyze the distinctions between LAMBDA and related approaches, including MetaGPT and ChatGPT-Advanced Data Analysis. Section E presents additional details on the datasets, while Section F presents multiple case studies, demonstrating LAMBDA’s capabilities in data analysis, self-correction mechanisms, human intelligence integration, educational applications, and report generation. Finally, Section G outlines the experimental setup.

A Function Calling Based Agent System

Our initial idea was to implement function calling. We developed extensive APIs that encompass a wide range of data processing and machine learning functionalities, including statistical descriptions (e.g., mean, median, standard deviation), encoding schemes (e.g., one-hot encoding, ordinal encoding), data partitioning, and model training (e.g., logistic regression, decision tree). We utilized five function libraries to build these APIs, each tailored for different purposes: the Data Description Library, Data Visualization Library, Data Processing Library, Modeling Library, and Evaluation Library. Each library caches variables such as processed data and models throughout the program’s lifecycle. The framework and workflow are illustrated in Figure S.1.

We implemented the function calling service by ReAct. Specifically, when prompted to generate text up to the “Observation” section, the LLM should halt generation at this point. This is essential as the “Observation” section requires the outcome of API execution to prevent LLMs from generating results autonomously. The details are depicted in Figure S.2.

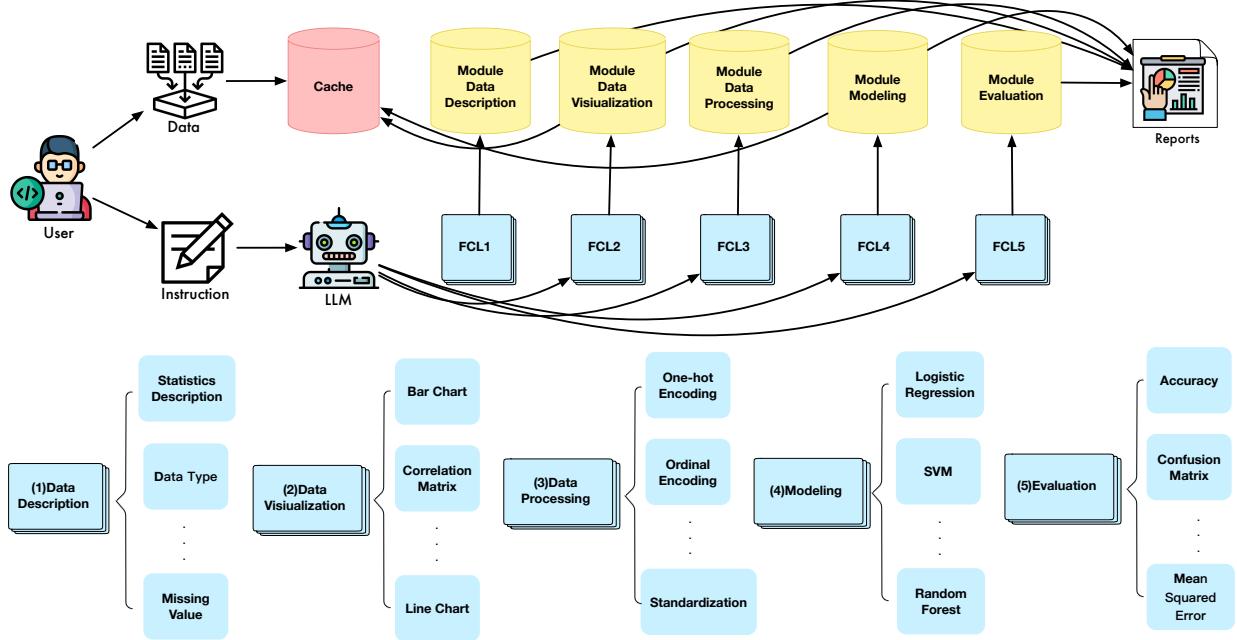


Figure S.1: Agent system design by the function calling method. The FCL means function calling library.

However, during the implementation, we found the function calling based data agent have some drawbacks and are engineering impractical.

- The function-calling method requires APIs to be pre-defined in advance. It is easy to imagine that the number of APIs required for statistical analysis and data processing across various scenarios is virtually limitless, making this approach impractical.
- In applications, a large number of APIs are typically required. These APIs often have complex interrelationships and extensive annotations. Such lengthy API annotations can result in sequences that exceed the maximum processing capacity of current LLMs, leading to the truncation of context.
- The model's ability to accurately select APIs diminishes as the number of available APIs increases. This decline is due to the increased complexity introduced by the growing number of APIs that LLMs need to evaluate. An incorrect choice of tools or models can directly lead to erroneous results and answers.

Building upon these conjectures, we have designed some experiments to verify it.

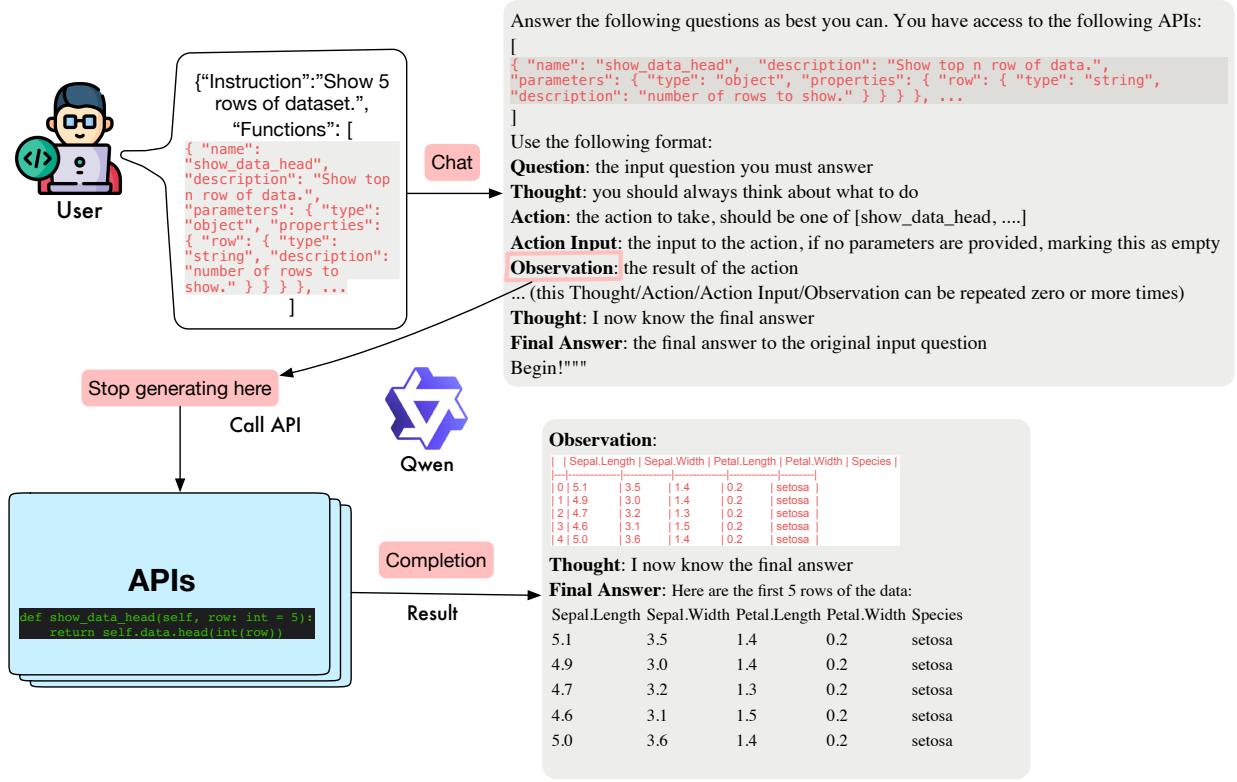


Figure S.2: Workflow of function calling service, demonstrated by Qwen1.5 and ReAct.

A.1 Challenges of the function-calling method

We estimate the maximum number of APIs that some open-source LLMs can handle in data analysis by using the average length of the pre-defined APIs. Figure S.3 illustrates the results. Qwen1.5 and Mistral-v0.1 were specifically designed to handle lengthy sequences, capable of managing 400 and 372 APIs, respectively. However, general-purpose LLMs such as LLaMA2, LLaMA3, Mistral-V0.2, Qwen1, ChatGLM2, and ChatGLM3 can process fewer than 100 APIs. This limitation poses a challenge for applications requiring a larger number of APIs, such as data analysis tasks.

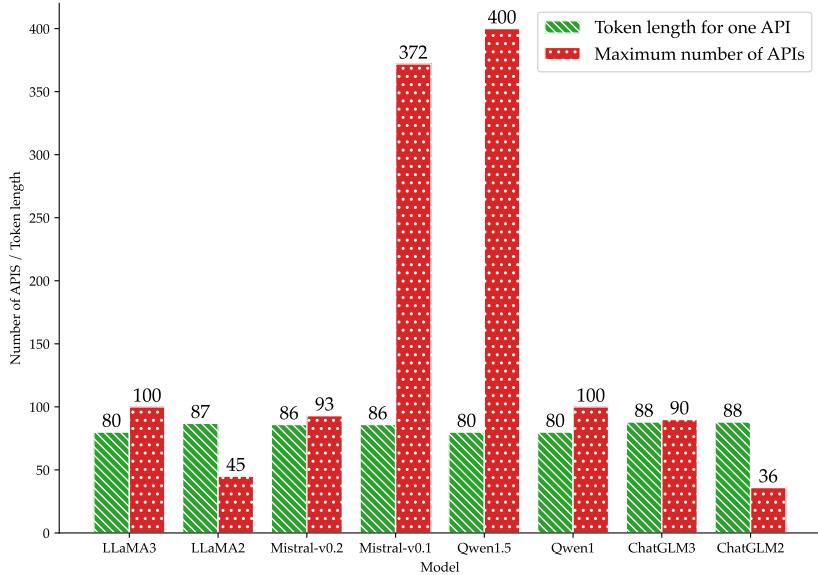


Figure S.3: Average token length for one API and maximum number of APIs each LLM can process.

To investigate the impact of the number of APIs on the accuracy of LLMs in selecting the correct APIs, we constructed a dataset comprising 100 commonly used APIs in data analysis. Using few-shot learning, we generated 880 testing instructions aligned with these APIs using Qwen1.5-110B. We then segmented both the APIs and testing instructions into intervals of 10 functions for analysis. The details of the evaluation dataset are shown in Table S.1, and the results are presented in Figure S.4.

Table S.1: Number of APIs and corresponding instructions in the evaluation dataset.

	APIs									
	10	20	30	40	50	60	70	80	90	100
Instructions	74	163	268	352	446	525	614	684	806	880

The results of API selection indicate a notable decline in the model's ability to accurately select APIs as the number of APIs increases. In the data science scenario, the number of APIs can be extensive due to it encompassing various processing methods and combinations.

In summary, the function-calling method exhibits several significant drawbacks. Firstly,

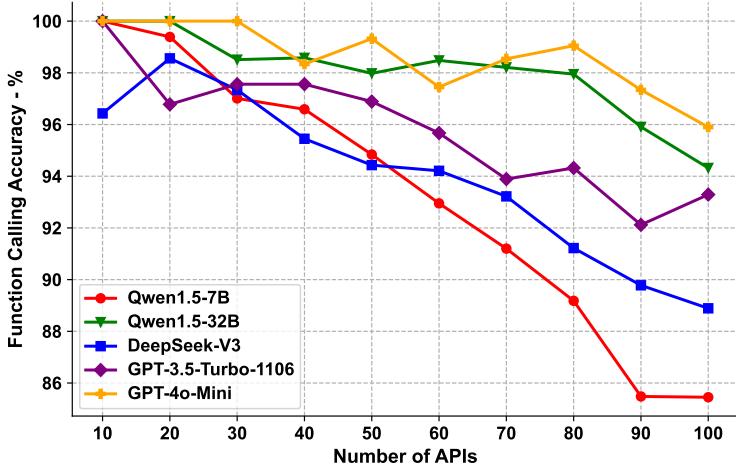


Figure S.4: The accuracy of API chosen by models Qwen, DeepSeek, and GPT series.

the labor-intensive process of defining numerous APIs is engineeringly impractical. Secondly, the static nature of APIs hinders adaptability to diverse and evolving user demands. Thirdly, extensive API annotations can occupy a substantial portion of the input sequence, potentially leading to truncation risks. Lastly, as the number of APIs increases, the model’s accuracy in correct selection decreases, thereby introducing potential inaccuracies in results.

A.2 Evaluation of the inspector agent

To assess the importance of the inspector agent in LAMBDA, we designed an ablation study using the heart disease dataset. This dataset, which contains missing values, naturally presents challenges. We utilized Qwen1.5-110B to generate instructions for related tasks. After filtering, there were 454 instructions in the experiment. We evaluated the execution pass rate with only a single agent (programmer) and two agents (programmer and inspector), respectively. The execution pass rate is a metric used to evaluate the reliability and effectiveness of a system, process, or code. It is calculated as:

$$\text{Execution Pass Rate} = \left(\frac{N_{\text{success}}}{N_{\text{total}}} \right) \times 100\%$$

where N_{success} is the number of successful executions and N_{total} is the total number of executions attempted. The results are summarized in Table S.2.

Table S.2: Experiment on single agent versus multiple agents. The percentages in brackets are the improvement rate over the single agent. Both the programmer and inspector agent are implemented by Qwen1.5-32b in this experiment.

Agents	Passing Rate %
programmer agent only	68.06
programmer + inspector	95.37 (40.13%)

The result shows a significant gap in the passing rate between using a programmer agent alone and incorporating an inspector. The programmer agent achieved a passing rate of 68.06%, while the integration of the inspector increased the passing rate to 95.37%, marking a substantial improvement of 40.13% over the single-agent setup. This experiment verified the crucial role of collaborative agents in enhancing the reliability and robustness of LAMBDA. By leveraging complementary strengths in error suggestion and correction, the multi-agent collaboration approach not only improves the code passing rate but also reduces the frequency of human intervention in executing data analysis tasks.

B Implementation of Kernel

The `CodeKernel` is designed to facilitate the execution of code within a Jupyter Notebook environment. It interacts with the Jupyter backend kernel to manage code execution, handle errors, and oversee the lifecycle of the kernel. This class provides an interface for executing code in a controlled manner, ensuring that outputs are captured and processed effectively.

B.1 Constructor

The constructor of the `CodeKernel` class initializes an instance of the kernel `kernel_name`, `kernel_id`, `kernel_config_path`, `python_path`, `ipython_path`, `init_file_path`, and `verbose`. The initialization process involves setting up environment variables based on the specified paths for Python or IPython, which are crucial for ensuring the correct execution context.

The kernel is initialized using the `KernelManager` from the `jupyter-client` library, allowing for granular control over the kernel’s operations. Depending on whether a configuration file is provided, the kernel is either started with the given settings or defaults are applied. The constructor also provides detailed logging of the kernel’s connection information if verbosity is enabled.

B.2 Code execution

The `execute` method is the primary mechanism for running code within the initialized kernel environment. This method sends a code string to the kernel for execution, utilizing a blocking client to ensure that the process completes before continuing. The method retrieves both shell messages and IOPub messages, which contain critical information about the execution status and outputs.

Outputs are processed to handle standard output (`stdout`), errors (`stderr`), and other response types from the kernel. The method returns a tuple consisting of the shell message and a list of processed output messages. This design allows for comprehensive handling of multi-line outputs and ensures that the relevant results are captured and returned.

B.3 Interactive execution

The `execute_interactive` method facilitates the execution of code in an interactive manner, where outputs are immediately accessible to the user. This method ensures that the code execution is monitored closely, with specific handling for timeout scenarios. If the `verbose` flag is set, the method provides detailed output about the execution process, aiding in debugging and analysis.

B.4 Code inspection

The `inspect` method allows for the introspection of code by sending it to the kernel and retrieving detailed information about variables, functions, and other elements within the code. This method is particularly useful for debugging, as it provides real-time insights into

the structure and behavior of the code being executed. The inspection results are returned as part of the shell message, which can be further processed or displayed.

B.5 Error handling

The `get_error_msg` and `check_msg` methods are responsible for handling errors that occur during code execution. The `get_error_msg` method extracts detailed error messages from the kernel's response, ensuring that these messages are accessible for debugging purposes. The `check_msg` method evaluates the status of the execution and prints error traces if any issues are detected, providing a clear indication of what went wrong during the execution.

B.6 Kernel management

The `CodeKernel` class includes several methods for managing the lifecycle of the kernel:

- `shutdown`: This method stops both the backend kernel and the associated code kernel, ensuring that all resources are released.
- `restart`: This method restarts the kernel, providing a clean slate for subsequent code executions.
- `start`: This method initializes the code kernel if it is not already running, allowing for new executions.
- `interrupt`: This method interrupts a long-running or unresponsive kernel, providing control over runaway processes.
- `is_alive`: This method checks whether the kernel is active and responsive, offering a way to monitor the kernel's status.

C Implementation of Knowledge Base

The key-value knowledge base serves as a repository containing various knowledge files (e.g., Python scripts). Users can extend the knowledge base by defining their own `Knw` class,

following our provided template and inheriting from the parent class. A typical `Knw` class includes the following attributes:

- `name`: The name of the knowledge.
- `description`: A summary outlining the functionality of the knowledge, which can be function illustration, and parameters of the knowledge.
- `mode`: The operational mode determines how the knowledge is applied, chosen from [‘core’, ‘full’].
- `theta`: A threshold parameter controlling the matching difficulty between user instructions and knowledge entries (optional).
- `core_function`: If `core` mode is selected, this field contains a use example illustrating how the knowledge should be applied. If `full mode` is selected, this field stores the complete implementation of the knowledge.
- `runnable_function`: If the `core` mode is selected, this section contains code that can be executed directly in the backend, such as function or class definitions, among other components (optional).

Additionally, the knowledge base allows users to perform maintenance and updates, ensuring the integration remains adaptable to evolving tasks and datasets.

A more clear example of the ‘full’ and ‘core’ mode workflow, which we present two examples from our experiments, is illustrated in Figures S.10 and Figure S.11.

D Discussion of LAMBDA, MetaGPT and ChatGPT-ADA

The LLM-based software agents like MetaGPT are designed to automatically build software programs like calculators, games, and websites. In MetaGPT, the workflow is complex since it consists of many roles in the team like product manager, Architect, Project Manager,

Engineer, and QA Engineer with much communication and collaboration in the team. So it usually costs more tokens and times to complete each task. However, the commonly used tasks in statistics and data analysis like drawing figures can be relatively easy to solve and do not need such a complicated process. To show this point, we use an example of a drawing figure. We record the time cost and token cost to show the big gap between the software agent and the data agent.

	Time	Token
MetaGPT	44.75s	19400
LAMBDA	7.35s	4146

Table S.3: Time cost and token cost of a plotting task in MetaGPT and LAMBDA. The token cost is based on prompt tokens and completion tokens

The results from Table S.3 show that software agents, such as MetaGPT, incur significant additional token usage and time when handling data analysis tasks, which is unnecessary. A more critical issue is that the output of software agents like MetaGPT consists of engineering files, such as Python scripts, which may require further manual configuration and execution by the user. In contrast, data analysis tasks demand intuitive, immediately interpretable results. Therefore, data agents offer a significant advantage in terms of interactivity within the domain of data analysis.

We also compare LAMBDA and ChatGPT in terms of several important features. The results are given in the Table S.4.

Table S.4: Comparison of LAMBDA and GPT-4-Advanced Data Analysis. Scalability means the agent can integrate domain knowledge like customized models or algorithms. Portability means the agent model is adapted to other LLMs like LLaMA3 and Qwen. Human-in-the-loop means users can intervene in outcomes.

	GPT-4-Advanced Data Analysis	LAMBDA
Coding-free	✓	✓
Scalability	✗	✓
Portability	✗	✓
Human-in-the-loop	✗	✓
Code exporting	✗	✓
Security	lower	higher
Report generation	Inconvenient by prompt	Convenient

These experiments show that LAMBDA outperforms GPT-4-Advanced Data Analysis in multiple features, highlighting the advantages of LAMBDA for data analysis tasks.

E Datasets

Here we give the information on the sources of the datasets used in our experiments and case studies.

Table S.5: Datasets used in this study.

DataSets	Usage
AIDS Clinical Trials Group Study 175 ¹	Classification
NHANES ²	Classification
Breast Cancer Wisconsin ³	Classification
Wine ⁴	Classification
Concrete Compressive Strength ⁵	Regression
Combined Cycle Power Plant ⁶	Regression
Abalone ⁷	Regression - Education Case Study
Airfoil Self-Noise ⁸	Regression
Iris ⁹	Classification - Data Analysis Case Study
Heart Disease ¹⁰	Regression - Education Case Study, Missing Data
Genomic Datasets ¹¹	High Dimensional Data
Framingham Heart Study Dataset ¹²	Missing Data
Student Admission Records ¹³	Missing Data
MINIST ¹⁴	Image Data
SMS Spam ¹⁵	Text Data

¹ <https://archive.ics.uci.edu/dataset/890/aids+clinical+trials+group+study+175>

² [https://archive.ics.uci.edu/dataset/887/national+health+and+nutrition+health+survey+2013-2014+\(nhanes\)+age+prediction+subset](https://archive.ics.uci.edu/dataset/887/national+health+and+nutrition+health+survey+2013-2014+(nhanes)+age+prediction+subset)

³ <https://archive.ics.uci.edu/dataset/891/cdc+diabetes+health+indicators>

⁴ <https://archive.ics.uci.edu/dataset/109/wine>

⁵ <https://archive.ics.uci.edu/dataset/165/concrete+compressive+strength>

⁶ <https://archive.ics.uci.edu/dataset/294/combined+cycle+power+plant>

⁷ <https://archive.ics.uci.edu/dataset/1/abalone>

⁸ <https://archive.ics.uci.edu/dataset/291/airfoil+self+noise>

⁹ <https://archive.ics.uci.edu/dataset/53/iris>

¹⁰ <https://archive.ics.uci.edu/dataset/45/heart+disease>

¹¹ <https://www.kaggle.com/datasets/anhpkn1/high-dimensional-data/data>

¹² <https://www.kaggle.com/datasets/aasheesh200/framingham-heart-study-dataset/data>

¹³ <https://www.kaggle.com/datasets/mohansacharya/graduate-admissions>

¹⁴ <https://www.kaggle.com/datasets/hojjatk/mnist-dataset>

¹⁵ <https://www.kaggle.com/datasets/uciml/sms-spam-collection-dataset/data>

The Genomic datasets include the following three datasets: TCGAmirna (Bentink et al., 2012), EMTAB386 (Colaprico et al., 2015), and GSE49997 (Pils et al., 2012). A brief description of these datasets are as follows.

- The TCGAmirna dataset contains 554 patients with high-grade serous ovarian cancer, which consists of 554 samples and 802 gene features (Bentink et al., 2012).
- The EMTAB386 dataset contains angiogenic mRNA and microRNA gene expression signature on 129 advanced stage, high grade serous ovarian cancers, which consists of 129 samples and 10360 gene features (Colaprico et al., 2015).
- The GSE49997 dataset contains the expression values of 204 epithelial ovarian cancer patients, which consists of 194 samples and 16051 gene features (Pils et al., 2012).

F Case studies

This section presents several case studies demonstrating the use of LAMBDA, including data analysis, a self-correcting mechanism, the integration of human intelligence, its application in education, and report generation.

Data Analysis

HUMAN	LAMBDA
1 Encoding the target `Species` to number like 0,1,2	<pre>"python import pandas as pd # Load the dataset data = pd.read_csv('xxx/cache/conv_cache/2c23cf4b-31a8-4aeb-8689-13b9fbdb7fc-2024-04-29/iris.csv') # Encode the target variable from sklearn.preprocessing import LabelEncoder label = LabelEncoder() label.fit_transform(data['Species']) # Display the encoded values data['Species'].head()</pre> <p>Execution result:</p> <pre>0 0 1 0 2 0 3 0 4 0</pre> <p>The target variable `Species` has been successfully encoded to numerical values 0, 1, and 2. This encoding will facilitate the use of the variable in various machine learning algorithms and analyses. Now that the target variable is encoded, you can proceed with further data preprocessing, model building, or analysis as needed.</p>
2 Draw a correlation matrix	<pre>"python import seaborn as sns import matplotlib.pyplot as plt # Create a correlation matrix correlation_matrix = data.corr() # Plot the correlation matrix plt.figure(figsize=(8, 6)) sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm', cbar=True) plt.title('Correlation Matrix') plt.savefig('xxx/cache/conv_cache/2c23cf4b-31a8-4aeb-8689-13b9fbdb7fc-2024-04-29/correlation_matrix.png')</pre> <p>Execution result:</p> <p>The correlation matrix has been successfully plotted using a heatmap. The heatmap visually represents the correlation coefficients between different features in the dataset. This information can be useful for understanding the relationships between the variables and identifying potential multicollinearity.</p> <p>The resulting correlation matrix plot has been saved as a PNG file, and it provides a clear visualization of the correlations between the features in the dataset. Further analysis or modeling can be informed by the insights gained from this correlation matrix.</p>
3 Split the data to train and test with a proportion of 8:2	<pre>"python from sklearn.model_selection import train_test_split # Separate the features and the target variable X = data.drop('Species', axis=1) y = data['Species'] # Split the data into training and testing sets X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)</pre> <p>Execution result:</p> <p>The dataset has been split into training and testing sets with a proportion of 80% for training data and 20% for testing data. This is a common split ratio for training and evaluating machine learning models. The training set (<code>X_train</code> and <code>y_train</code>) can be used to train the model, while the testing set (<code>X_test</code> and <code>y_test</code>) can be used to evaluate the model's performance and generalization to new data.</p> <p>You can now use the <code>'X_train'</code>, <code>'X_test'</code>, <code>'y_train'</code>, and <code>'y_test'</code> datasets for training and evaluating machine learning models.</p>
4 Train a logistic regression model and evaluate it by accuracy on the test set.	<pre>"python from sklearn.linear_model import LogisticRegression from sklearn.metrics import accuracy_score # Initialize the logistic regression model logreg_model = LogisticRegression(max_iter=1000) # Train the model on the training data logreg_model.fit(X_train, y_train) # Make predictions on the test data y_pred = logreg_model.predict(X_test) # Evaluate the model using accuracy accuracy = accuracy_score(y_test, y_pred) accuracy</pre> <p>Execution result:</p> <pre>1.0</pre> <p>The logistic regression model has been trained and evaluated on the test set, yielding an accuracy of 1.0 or 100%. An accuracy of 1.0 indicates that the model predicted the classes of all samples in the test set perfectly.</p> <p>While achieving a high accuracy is desirable, it is important to consider the possibility of overfitting. In this case, the high accuracy on the test set may indicate overfitting. It's recommended to further evaluate the model's performance using techniques such as cross-validation, precision-recall analysis, or confusion matrix to gain a deeper understanding of its predictive capabilities.</p> <p>Additionally, given the small size of the Iris dataset, a high accuracy on the test set is not unexpected. It would be advisable to use more complex datasets for a more realistic assessment of model performance.</p>

Figure S.5: Case study: Analysis of Iris dataset.

Data Analysis

HUMAN	LAMBDA
5 Train a svm model and evaluate it by accuracy on the test set.	<pre>'''python from sklearn.svm import SVC # Initialize the SVM model svm_model = SVC(kernel='linear') # Train the model on the training data svm_model.fit(X_train, y_train) # Make predictions on the test data y_pred_svm = svm_model.predict(X_test) # Evaluate the model using accuracy accuracy_svm = accuracy_score(y_test, y_pred_svm) accuracy_svm ''' Execution result: 1.0 The support vector machine (SVM) model with a linear kernel has been trained and evaluated on the test set, yielding an accuracy of 1.0 or 100%. Similar to the logistic regression model, an accuracy of 1.0 may indicate overfitting. As mentioned previously, it's advised to further evaluate the model's performance using additional techniques and metrics such as cross-validation, precision-recall analysis, or confusion matrix to gain a more comprehensive understanding of its predictive capabilities. While high accuracy is desirable, it is important to maintain a critical perspective and consider the potential for overfitting in the context of the specific dataset and model evaluation.*</pre>
6 Train a mlp model and evaluate it by accuracy on the test set.	<pre>'''python from sklearn.neural_network import MLPClassifier # Initialize the MLP model mlp_model = MLPClassifier(hidden_layer_sizes=(100, 50), max_iter=500) # Train the model on the training data mlp_model.fit(X_train, y_train) # Make predictions on the test data y_pred_mlp = mlp_model.predict(X_test) # Evaluate the model using accuracy accuracy_mlp = accuracy_score(y_test, y_pred_mlp) accuracy_mlp ''' Execution result: 1.0 The multi-layer perceptron (MLP) model has been trained and evaluated on the test set, resulting in an accuracy of 1.0 or 100%. As with the previous models, achieving an accuracy of 1.0 may indicate potential overfitting. In practice, it is important to critically assess the model's performance using a variety of evaluation metrics and techniques, as well as cross-validation, to ensure a robust assessment. It's worth considering other evaluation metrics such as precision, recall, and F1 score to gain a more comprehensive understanding of the model's performance characteristics. Additionally, exploring techniques for optimizing the model's architecture, regularization, and hyperparameters could further enhance its generalization capabilities.*</pre>
7 Train a decision tree model and evaluate it by accuracy on the test set.	<pre>'''python from sklearn.tree import DecisionTreeClassifier # Initialize the decision tree model dt_model = DecisionTreeClassifier() # Train the model on the training data dt_model.fit(X_train, y_train) # Make predictions on the test data y_pred_dt = dt_model.predict(X_test) # Evaluate the model using accuracy accuracy_dt = accuracy_score(y_test, y_pred_dt)\naccuracy_dt accuracy_dt ''' Execution result: 1.0 The decision tree model has been trained and evaluated on the test set, resulting in an accuracy of 1.0 or 100%. It's important to consider that achieving a high accuracy score on a small and well-structured dataset like the Iris dataset may indicate overfitting. Given the perfect accuracy, it's recommended to further evaluate the model's performance using additional techniques such as cross-validation, precision-recall analysis, or confusion matrix to gain a more comprehensive understanding of its predictive capabilities. It's also important to take into account the interpretability of the decision tree model and how it aligns with the specific requirements of the analysis or application. Further model tuning and exploration of ensemble methods may also be beneficial for improving generalization and ensuring robust performance on new data.*</pre>
8 train a random forest model and evaluate it by accuracy on the test set.	<pre>'''python from sklearn.ensemble import RandomForestClassifier # Initialize the random forest model rf_model = RandomForestClassifier(n_estimators=100, random_state=42) # Train the model on the training data rf_model.fit(X_train, y_train) # Make predictions on the test data y_pred_rf = rf_model.predict(X_test) # Evaluate the model using accuracy accuracy_rf = accuracy_score(y_test, y_pred_rf) accuracy_rf ''' Execution result: 1.0 The random forest model has been trained and evaluated on the test set, resulting in an accuracy of 1.0 or 100%. As with previous models, it's important to remain cautious about the potential for overfitting when achieving a perfect accuracy score, especially on a small dataset like Iris. While a high accuracy score is desirable, it's essential to consider the model's generalization to new data. Additional evaluation metrics, cross-validation, and further analysis of model performance can provide a more comprehensive understanding of the random forest model's capabilities. In addition to accuracy, it would be beneficial to explore other evaluation metrics and techniques such as precision, recall, and F1 score, as well as feature importance analysis, to gain insights into the model's predictive performance and behavior.*</pre>

Figure S.6: Cont. Case study: Analysis of Iris dataset.

Data Analysis

HUMAN

- 9 Use GridSearchCV to find the best hyperparameters of mlp in a parameters group. you can define the search group by yourself, 5 group is enough.

```
"""
python
from sklearn.model_selection import GridSearchCV

# Define the parameter grid for the MLP model
param_grid_mlp = [
    {
        'hidden_layer_sizes': [(50), (100), (50, 50), (100, 50), (100, 100)],
        'activation': ['logistic', 'tanh', 'relu'],
        'solver': ['adam', 'sgd'],
        'max_iter': [200, 500, 1000]
    }
]
# Initialize the MLP model
mlp_model = MLPClassifier()

# Initialize and fit the GridSearchCV
grid_search_mlp = GridSearchCV(mlp_model, param_grid_mlp, cv=5, scoring='accuracy', n_jobs=-1)
grid_search_mlp.fit(X_train, y_train)

# Get the best parameters and the best accuracy score
best_params_mlp = grid_search_mlp.best_params_
best_score_mlp = grid_search_mlp.best_score_

best_params_mlp, best_score_mlp
"""

Execution result:
({'activation': 'tanh', 'hidden_layer_sizes': (100,), 'solver': 'sgd', 'max_iter': 200}, 0.975)

The best hyperparameters for the MLP model identified through GridSearchCV are as follows:
- Activation function: 'tanh'
- Hidden layer sizes: (100,)
- Maximum number of iterations: 200
- Solver: 'sgd'

The best accuracy score achieved using these hyperparameters is 0.975. This grid search process provides valuable insights into the combination of hyperparameters that optimizes the MLP model's performance on the training data.

Using the best hyperparameters identified, you can retrain the MLP model and evaluate its performance on the test set to ascertain its generalization and predictive capabilities. Additionally, a more in-depth analysis of the model's performance, such as precision-recall analysis and model interpretation, can provide further insights into its behavior and characteristics."

```

- 10 Good, save all models before

```
"""
python
import joblib

# Save the trained models
model_files = [
    'logistic_regression_model.pkl': logreg_model,
    'svm_model.pkl': svm_model,
    'mlp_model.pkl': mlp_model,
    'decision_tree_model.pkl': dt_model,
    'random_forest_model.pkl': rf_model
]

for file_name, model in model_files.items():
    joblib.dump(model, file_name)

# Save the best MLP model from GridSearchCV
joblib.dump(grid_search_mlp.best_estimator_, 'best_mlp_model.pkl')

Execution result:
logistic_regression_model.pkl
svm_model.pkl
decision_tree_model.pkl
random_forest_model.pkl
best_mlp_model.pkl

The trained models have been successfully saved. Additionally, the best MLP model resulting from the GridSearchCV process has been saved as 'best_mlp_model.pkl'. These saved model files can be used for future predictions, analysis, or deployment without the need to retrain the models from scratch.

If you need to transfer these models to another location or share them with others, you can download the files and store them in a location of your choice.\n\nIf you have any further questions or need additional assistance, feel free to ask!
decision_tree_model.pkl
best_mlp_model.pkl
logistic_regression_model.pkl
svm_model.pkl
random_forest_model.pkl
mlp_model.pkl

```

Figure S.7: Cont. Case study: Analysis of Iris dataset.

Self-correcting mechanism

Instruction: Draw a confusion matrix

Programmer response [Code]

```
import seaborn as sns
import matplotlib.pyplot as plt
# Calculate the correlation matrix
correlation_matrix = data.corr()
# Create a heatmap of the correlation matrix
plt.figure(figsize=(8, 6))
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm')
plt.title('Correlation Matrix')
plt.savefig('correlation_matrix.png')
```

Inspector prompt

You are an experienced and insightful inspector, and you need to identify the bugs in the given code based on the error messages and give modification suggestions.

- bug code:

[Code]

When executing above code, errors occurred:

[Error message]

Please check the implementation of the function and provide a method for modification based on the error message. No need to provide the modified code.

Modification method:

Repair prompt for programmer

You should attempt to fix the bugs in the bellow code based on the provided error information and the method for modification. Please make sure to carefully check every potentially problematic area and make appropriate adjustments and corrections.

- bug code: [Code]

When executing above code, errors occurred:

[Error message]

Please check the implementation of the function and fix the code based on the modification method.

- modification method:

[Fix_method]

The code you modified (should be wrapped in ``python``):

Execution message [Error message]

```
ValueError Traceback (most recent call last)
Cell In[4], line 5
      2 import matplotlib.pyplot as plt
      4 # Calculate the correlation matrix
----> 5 correlation_matrix = data.corr()
      7 # Create a heatmap of the correlation matrix
      8 plt.figure(figsize=(8, 6))

.....
ValueError: could not convert string to float: 'setosa'
```

Inspector response [Fix_method]

The error message "could not convert string to float: 'setosa'" indicates that there are non-numeric values present in the data that is causing the problem. To resolve this issue, you can consider the following modification method: Check the columns of the data and identify if there are any non-numeric columns that are causing the problem. It's possible that the 'species' column in the 'iris' dataset contains non-numeric values. You can either remove the non-numeric columns or convert them into numeric format if they contain categorical data. For example, you can use one-hot encoding or label encoding to convert categorical data into numeric format. Once the non-numeric values are processed, the correlation matrix should be computed without any issues.

Programmer response

```
```python
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
Check the data to identify non-numeric columns
print(data.dtypes)
Convert categorical data to numeric format using one-hot encoding
data = pd.get_dummies(data, columns=['Species'], drop_first=True)
Draw a correlation matrix after processing non-numeric data
correlation_matrix = data.corr()
plt.figure(figsize=(8, 6))
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm')
plt.title('Correlation Matrix')
plt.savefig('correlation_matrix.png')
```

```

Execution result

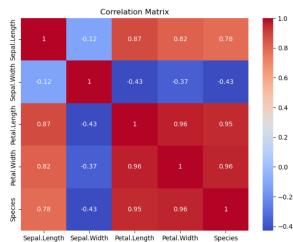


Figure S.8: Case study: An example of self-correcting mechanism in LAMBDA.

Knowledge Integration (knowledge Base)

| Nearest Correlation Matrix | Knowledge Base - Interface |
|--|---|
| <p>Paper: Houduo Qi and Defeng Sun. A quadratically convergent newton method for computing the nearest correlation matrix. SIAM Journal on Matrix Analysis and Applications, 28(2):360–385, 2006</p> <p>Python code: https://www.polyu.edu.hk/ama/profile/dfsun/CorrelationMatrix.py</p> | <pre> def NearestCorrelationMatrix(g_input, b_input=None, tau=None, tol=None): print('-- Semismooth Newton-CG method starts --\n') return x_result, y def my_gradient(y_input, lamb, p_input, b_0, n): f = 0.0 return f, Fy def my_issorted(x_input, flag): n = x_input.size return tf_value def my_jacobian_matrix(x, omega_12, p_input, n): x_result = np.zeros((n, 1)) return x_result def my_mexeig(x_input): [n, m] = x_input.shape return p_x, lamb def my_omega_mat(p_input, lamb, n): idx_idp = np.where(lamb > 0) return omega_12 def my_pca(x_input, lamb, p_input, b_0, n): x_pca = x_input return x_pca def my_pre_cg(b, tol, maxit, c, omega_12, p_input, n): # Initializations return p, flag, relres, iterk def my_precond_matrix(omega_12, p_input, n): [r, s] = omega_12.shape return c def test_ncm(): # test n = 3000 data_g_test = scipy.randn(n, n) data_g_test = (data_g_test + data_g_test.transpose()) / 2.0 data_g_test = data_g_test - np.diag(np.diag(data_g_test)) + np.eye(n) b = np.ones((n, 1)) tau = 0 tol = 1.0e-6 [x_test_result, y_test_result] = NearestCorrelationMatrix(data_g_test, b, tau, tol) print("The x_test_result: \n", x_test_result) print() print("The y_test_result: \n", y_test_result) </pre> |

Figure S.9: Case study: An example of integrating human intelligence in the analysis. The red part is the ‘core’ function in the ‘Core’ mode.

Knowledge Integration (Full)

| HUMAN | LAMBDA |
|--|--|
| <p>I want to use PAMI Library to perform pattern mining on transactional databases.</p> <p>Using the data of 'https://u-aizu.ac.jp/~udayrage/datasets/transactionalDatabases/Transactional_T10I4D100K.csv'.</p> <p>Set minSup by 500 and use FP-Growth as the algorithm.</p> <p>Save the mined frequent patterns to a file, retrieve the patterns as a DataFrame, and display the total number of patterns, runtime, and memory usage details.</p> | <p>Retrieval: The retriever found the following pieces of code that may help address the problem. You should refer to this code and modify it as appropriate.</p> <p>Retrieval code in 'full' mode:</p> <pre>Description of the code: The pami library is a Python library for pattern mining</pre> <p>Full code :</p> <pre>```python !pip install PAMI from PAMI.frequentPattern.basic import FPGrowth as alg fileURL = "https://u-aizu.ac.jp/~udayrage/datasets/transactionalDatabases/Transactional_T10I4D100K.csv" minSup = 300 obj = alg.FP_Growth(ifile=fileURL, minSup=minSup, sep='\t') #here is sep=' ' # obj.startMine() #deprecated obj.mine() obj.save('frequentPatternsAtMinSupCount300.txt') frequentPatternsDF = obj.getPatternsAsDataFrame() print('Total No of patterns: ' + str(len(frequentPatternsDF))) # print the total number of patterns print('Runtime: ' + str(obj.getRuntime())) # measure the runtime print('Memory (RSS): ' + str(obj.getMemoryRSS())) print('Memory (USS): ' + str(obj.getMemoryUSS())) ``` </pre> <p>Your modified code:</p> <pre>```python !pip install PAMI from PAMI.frequentPattern.basic import FPGrowth as alg # Define the file URL and minimum support fileURL = "https://u-aizu.ac.jp/~udayrage/datasets/transactionalDatabases/Transactional_T10I4D100K.csv" minSup = 500 # Initialize the FP_Growth algorithm with specified parameters obj = alg.FP_Growth(ifile=fileURL, minSup=minSup, sep='\t') # Note: sep='\t' for tab separation # Perform the mining of frequent patterns obj.mine() # Save the mined frequent patterns to a file obj.save('/xxx/frequentPatternsAtMinSupCount500.txt') # Retrieve the patterns as a DataFrame frequentPatternsDF = obj.getPatternsAsDataFrame() # Display the total number of patterns, runtime, and memory usage details print('Total No of patterns: ' + str(len(frequentPatternsDF))) # Print the total number of patterns print('Runtime: ' + str(obj.getRuntime())) # Measure the runtime print('Memory (RSS): ' + str(obj.getMemoryRSS())) # Measure memory RSS print('Memory (USS): ' + str(obj.getMemoryUSS())) # Measure memory USS ``` </pre> <p>Execute code...</p> <p>Execute result:</p> <pre>Frequent patterns were generated successfully using frequentPatternGrowth algorithm Total No of patterns: 1072 Runtime: 84.63605189323425 Memory (RSS): 615.170.048 B Memory (USS): 561.594.368 B</pre> <p>Metric Value</p> <pre>Total Number of Patterns 1072 Runtime (seconds) 84.64 Memory (RSS) 615.170.048 B Memory (USS) 561.594.368 B</pre> <p>The mined dataset has produced a total of 1072 frequent patterns with a runtime of approximately 84.64 seconds. Memory usage was substantial, with a Resident Set Size (RSS) of approximately 615 MB and an Unshared Set Size (USS) of about 561 MB.</p> <p>Next steps could involve analyzing the frequent patterns to identify significant trends or associations, or evaluating the mining results by visualizing them for better insights.</p> <pre>frequentPatternsAtMinSupCount500.txt</pre> |

Figure S.10: An illustration of integrating knowledge in 'full' mode.

Knowledge Integration (Core)

| HUMAN | LAMBDA |
|--|--|
| <p>I want to calculate the nearest correlation matrix by the Quadratically Convergent Newton Method. Please write a well-detailed code. The code gives details of the computation for each iteration, such as the norm of gradient, relative duality gap, dual objective function value, primal objective function value, and the running time.</p> <p>Using the following parameters to run a test case and show the result:</p> <p>Set a 2000x2000 random matrix whose elements are randomly drawn from a standard normal distribution, the matrix should be symmetric positive, and semi-definite.</p> <p>Set the b vector by 2000x1 with all elements 1.</p> <p>Set tau by 0.1, and tolerance error by 1.0e-7.</p> | <p>Retrieval:\nThe retriever found the following pieces of code cloud address the problem. All functions and classes have been defined and executed in the back-end.</p> <p>Retrieval code in 'core' mode:</p> <p>Description of the code: The function calculates the nearest correlation matrix</p> <p>Defined and executed code in the back-end:</p> <pre> def NearestCorrelationMatrix(g_input, b_input=None, tau=None, tol=None): back-end executed print("-- Semismooth Newton-CG method starts --\n") return x_result, y ]</pre> <p>Core code (Refer to this core code, note all functions and classes have been defined in the back-end, you can directly use them):</p> <pre>'''python n = 3000 data_g_test = scipy.randn(n, n) data_g_test = (data_g_test + data_g_test.transpose()) / 2.0 data_g_test = data_g_test - np.diag(np.diag(data_g_test)) + np.eye(n) b = np.ones((n, 1)) tau = 0 tol = 1.0e-6 [x_test_result, y_test_result] = self.NearestCorrelationMatrix(data_g_test, b, tau, tol) ... '''</pre> <p>Your code:</p> <pre>'''python import numpy as np import scipy.linalg as la</pre> <p># Set the parameters</p> <pre>n = 2000 g_input = np.random.randn(n, n) g_input = (g_input + g_input.transpose()) / 2.0 g_input = g_input - np.diag(np.diag(g_input)) + np.eye(n) b_input = np.ones((n, 1)) tau = 0.1 tol = 1.0e-7 # Run the test case x_test_result, y_test_result = NearestCorrelationMatrix(g_input, b_input, tau, tol)</pre> <p>print("The x_test_result: \n", x_test_result) print() print("The y_test_result: \n", y_test_result) ''' <p>This code sets the parameters n, g_input, b_input, tau, and tol according to the problem statement. It then calls the NearestCorrelationMatrix function with these parameters and prints the results.</p> <p>Note that I didn't modify the NearestCorrelationMatrix function itself, as it seems to be a complex implementation of the Semismooth Newton-CG method. I only provided the test case code to run the function with the given parameters.</p> <p><input type="checkbox"/> Execute code...</p> <p><input checked="" type="checkbox"/> Execute result:</p> <p>-- Semismooth Newton-CG method starts --</p> <p>Newton-CG: Initial Dual objective function value: [1475528.24357215]</p> <p>Newton-CG: Initial Primal objective function value: 933281.3129374245</p> <p>Newton-CG: Norm of Gradient: 579.6794822761284</p> <p>Newton-CG: computing time used so far: 10.611207962036133</p> <p>Newton-CG: Number of CG Iterations==== 1</p> <p>The x_test_result:</p> <pre>[[1. -0.03941701 0.03307246 ... -0.01731567 -0.11538529 -0.01449621] [-0.03941701 1. -0.02205682 ... 0.14064247 0.01924966 -0.03100769] [0.03307246 -0.02205682 1. ... 0.03770609 0.04565391 0.00780341] ... The y_test_result: [[-46.71400534] [-41.15359542] [-44.00442815] ... Based on the executing result, the Semismooth Newton-CG method converged to a solution with a relative duality gap of 3.15279506e-08. The final optimal solution has a rank of 214. The computation time used for equal weight calibration is 47.19361400604248 seconds.</pre> </p> |

Figure S.11: An illustration of integrating knowledge in 'core' mode.

Education (Lecture and Homework Design)

Teacher View

I am a teacher. I will teach lasso in next class, totally 2 hours. You should write a syllabus for me. Besides, you should also design an experiment task for students to learn Lasso. Use the datasets like Abalone: <https://archive.ics.uci.edu/dataset/1/abalone>

LAMBDA

Course Outline:

Title: Introduction to Lasso Regression

Duration: 2 hours

I. Introduction to Lasso Regression

- A. Overview of regression analysis
- B. Introduction to Lasso regression
- C. Advantages and disadvantages of Lasso regression

II. Understanding Lasso Regression

- A. Understanding the L1 regularization
- B. Comparison with traditional regression techniques
- C. Use cases and applications

III. Implementing Lasso Regression

- A. Data preprocessing for Lasso regression
- B. Training Lasso regression model
- C. Evaluating model performance

IV. Advanced Topics

- A. Hyperparameter tuning
- B. Cross-validation for model selection
- C. Dealing with multicollinearity

V. Case Studies and Practical Applications

- A. Real-world examples of Lasso regression
- B. Discussion on potential research areas

Experiment Task:

Task: Prediction of Abalone Age using Lasso Regression

Objective: The objective of this experiment is to apply Lasso regression on the Abalone dataset to predict the age of abalone based on various physical measurements.

Dataset: Abalone dataset can be downloaded from <https://archive.ics.uci.edu/dataset/1/abalone> or any other dataset containing physical measurements of abalone and their ages.

Steps:

Data Preprocessing:

Load the dataset and inspect the features and target variable

Perform any necessary data cleaning or preprocessing

Exploratory Data Analysis:

Visualize the relationship between the features and target variable

Analyze correlations and distributions of the variables

Implementing Lasso Regression:

Split the dataset into training and testing sets

Implement Lasso regression using a suitable library (e.g., scikit-learn in Python)

Train the model on the training set and evaluate its performance on the testing set

Model Evaluation:

Evaluate the performance of the Lasso regression model using appropriate metrics (e.g., mean squared error, R-squared)

Advanced Analysis:

Experiment with different values of alpha (regularization parameter) to understand its impact on the model

Perform cross-validation to select the best model

Homework:

Students will be tasked with writing a summary of the key concepts and advantages of Lasso regression compared to traditional regression techniques.

Students will apply Lasso regression to a different dataset of their choice and write a report on their findings, including model performance and insights gained from the analysis.

Figure S.12: Case study: LAMBDA in education. We use teaching Lasso as an example.

Education (Do Homework on LAMBDA)

STUDENT

LAMBDA

- 1 This is Abalone datasets. I want to predict the age of Abalone, corresponding column is Ring. First, show 5 rows of the datasets.

```
```python
Load the Abalone datasets
import pandas as pd
data = pd.read_csv('/xxx/cache/conv_cache/4e7d8506-6234-44b3-a177-aed15f488027-2024-05-20/Abalone.csv')

Show 5 rows of the datasets
data.head()
```
Execute result:  

Here is the rewritten table in markdown format:
```

| Sex | Length | Diameter | Height | Whole_weight | Shucked_weight | Viscera_weight | Shell_weight | Rings |
|-----|--------|----------|--------|--------------|----------------|----------------|--------------|-------|
| M | 0.455 | 0.365 | 0.095 | 0.5140 | 0.2245 | 0.1010 | 0.150 | 15 |
| M | 0.350 | 0.265 | 0.098 | 0.2255 | 0.0995 | 0.0485 | 0.070 | 7 |
| F | 0.530 | 0.420 | 0.135 | 0.6770 | 0.2565 | 0.1415 | 0.210 | 9 |
| M | 0.440 | 0.365 | 0.125 | 0.5160 | 0.2155 | 0.1140 | 0.155 | 10 |
| I | 0.330 | 0.255 | 0.080 | 0.2050 | 0.0895 | 0.0395 | 0.055 | 7 |

The dataset includes information about the sex, physical dimensions, and number of rings for abalones. The 'Rings' column can be used to predict the age of the abalones, as it represents the number of rings on the abalone shell. The next step would be to perform exploratory data analysis to understand the data distribution and relationships between variables. Additionally, feature engineering and model selection for age prediction can be explored.

- 2 Encoding column Sex as one-hot vectors and replace original column.

```
```python
Perform one-hot encoding on the 'Sex' column
data = pd.get_dummies(data, columns=['Sex'], drop_first=True)

Display the first 5 rows of the updated dataset
data.head()
```
Execute result:  

Here is the rewritten table in markdown format:
```

| Length | Diameter | Height | Whole_weight | Shucked_weight | Viscera_weight | Shell_weight | Rings | Sex_I | Sex_M |
|--------|----------|--------|--------------|----------------|----------------|--------------|-------|-------|-------|
| 0.455 | 0.365 | 0.095 | 0.5140 | 0.2245 | 0.1010 | 0.150 | 15 | False | True |
| 0.350 | 0.265 | 0.090 | 0.2255 | 0.0995 | 0.0485 | 0.070 | 7 | False | True |
| 0.530 | 0.420 | 0.135 | 0.6770 | 0.2565 | 0.1415 | 0.210 | 9 | False | False |
| 0.440 | 0.365 | 0.125 | 0.5160 | 0.2155 | 0.1140 | 0.155 | 10 | False | True |
| 0.330 | 0.255 | 0.080 | 0.2050 | 0.0895 | 0.0395 | 0.055 | 7 | True | False |

The 'Sex' column has been successfully encoded into one-hot vectors, replacing the original column with new columns 'Sex_I' and 'Sex_M'. This transformation will enable the machine learning models to interpret the 'Sex' attribute effectively. The next step would involve splitting the data into features and labels and proceeding with the model training process to predict the age of the abalones.

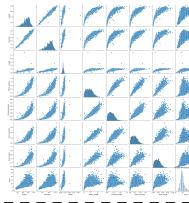
- 3 Visualize the relationship between the features and target variable. Save the figure finally.

```
```python
import seaborn as sns
import matplotlib.pyplot as plt

Plot the pairplot for the relationship between features and target variable
sns.pairplot(data, vars=['Length', 'Diameter', 'Height', 'Whole_weight', 'Shucked_weight', 'Viscera_weight', 'Shell_weight', 'Rings'])
plt.title('Pairplot of Features and Rings')
plt.savefig('/xxx/cache/conv_cache/4e7d8506-6234-44b3-a177-aed15f488027-2024-05-20/abalone_pairplot.png')
```
Execute result:  

/xxx/anaconda3/lib/python3.11/site-packages/seaborn/axisgrid.py:118: UserWarning: The figure layout has changed to tight
self._figure.tight_layout(*args, **kwargs)
```

The pairplot illustrates the pairwise relationships between the features and the target variable 'Rings'. It provides insights into the correlations and distribution of the features. The next steps could involve feature scaling, splitting the data into training and testing sets, and then training a predictive model to predict the age of the abalones.



- 4 Split the dataset into training and testing sets with a proportion of 8:2. Show the shape of the training and testing sets.

```
```python
from sklearn.model_selection import train_test_split

Split the dataset into training and testing sets
X = data.drop('Rings', axis=1) # Features
y = data['Rings'] # Target variable

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

Display the shape of the training and testing sets
print('Training set shape:', X_train.shape, y_train.shape)
print('Testing set shape:', X_test.shape, y_test.shape)
```
Execute result:  

Training set shape: (3341, 9) (3341)  

Testing set shape: (836, 9) (836)  

Training set shape: (3341, 9) (3341)  

Testing set shape: (836, 9) (836)  

The dataset has been successfully split into training and testing sets with a ratio of 80:20, resulting in 3341 samples in the training set and 836 samples in the testing set, with 9 features in each set. The next step would involve model training using the training set, followed by evaluating the model's performance on the testing set to predict the age of the abalones.
```

Figure S.13: Cont. Case Study: LAMBDA in education. Students complete assignment.

Education (Do Homework on LAMBDA)

STUDENT

LAMBDA

- 5 Implement Lasso regression using a suitable library (e.g., scikit-learn in Python) and train the lasso on the training set and evaluate its MSE on the testing set.

```
```
python
from sklearn.linear_model import Lasso
from sklearn.metrics import mean_squared_error

Initialize the Lasso regression model
lasso_model = Lasso(alpha=0.1)

Train the Lasso model on the training set
lasso_model.fit(X_train, y_train)

Make predictions using the trained model
y_pred = lasso_model.predict(X_test)

Calculate Mean Squared Error (MSE) on the testing set
mse = mean_squared_error(y_test, y_pred)
mse
```

Execute result:
7.2185794133162995

The Mean Squared Error (MSE) of the Lasso regression model on the testing set is 7.22. This value represents the average squared difference between the actual and predicted age of the abalones. The next step could involve further model evaluation, hyperparameter tuning, and exploring alternative regression models to improve performance.
```

- 6 Use grid_search_cv to perform cross-validation to select the best model with different values of alpha. Select alpha in [0.1, 0.5, 1, 1.5, 2]. Print the best parameters and best score (MSE). Set n_jobs=-1 and random_state=42. Save the best model finally.

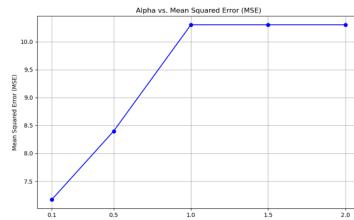
```
```
python
import matplotlib.pyplot as plt

Extract alpha values and corresponding MSE from the GridSearchCV results
alphas = [0.1, 0.5, 1, 1.5, 2]
mse_values = [-result for result in grid_search_cv_results_['mean_test_score']]

Create a line plot to show the relationship between alpha and MSE
plt.figure(figsize=(10, 6))
plt.plot(alphas, mse_values, marker='o', linestyle='-', color='b')
plt.title('Alpha vs. Mean Squared Error (MSE)')
plt.xlabel('Alpha')
plt.ylabel('Mean Squared Error (MSE)')
plt.xticks(alphas)
plt.grid(True)

Save the figure
plt.savefig('xxx/cache/conv_cache/4e7d8506-6234-44b3-a177-aed15f488027-2024-05-20/lasso_alpha_mse_plot.png')

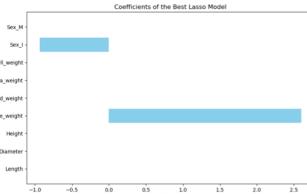
Execute result:
```



- 7 Draw a figure to show the coefficients of the best Lasso model.

```
```
python
# Plot the coefficients of the best Lasso model
plt.figure(figsize=(10, 6))
plt.bar(best_model_coef_index, best_model_coef['Coefficient'], color='skyblue')
plt.xlabel('Coefficient Value')
plt.ylabel('Features')
plt.title('Coefficients of the Best Lasso Model')
plt.savefig('xxx/cache/conv_cache/4e7d8506-6234-44b3-a177-aed15f488027-2024-05-20/lasso_coefficients_plot.png')

Execute result:
```



I have double-checked to code, and it seems there is no issue. The bar chart representing the coefficients of the best Lasso model has been successfully saved as 'lasso_coefficients_plot.png' in the specified directory. This visualization provides a clear view of the coefficients' values and their impact on the predictions, aiding in understanding the feature importance.

Figure S.14: Cont. Case study: LAMBDA in education. Students complete assignment.

Report Generation

Classification Task Using Wine Dataset with Machine Learning Models

1. Abstract:

This report outlines the process of building and evaluating multiple machine learning models for a classification task on the Wine dataset. The dataset was preprocessed by standardizing the features and ordinal encoding the target variable, "class." Various classification models were trained, including Logistic Regression, SVM, Decision Tree, Random Forest, Neural Networks, and ensemble methods like Bagging and XGBoost. Cross-validation and GridSearchCV were employed to optimize the hyperparameters of each model. Logistic Regression achieved an accuracy of 98.89%, while the best-performing models included Random Forest and SVM. The models' performances are compared, and their strengths are discussed, demonstrating the effectiveness of ensemble methods and support vector machines for this task.

2. Introduction

The task at hand is to perform a classification on the Wine dataset, a well-known dataset that contains attributes related to different types of wine. The goal is to correctly classify the wine type (target variable: "class") based on its chemical properties such as alcohol content, phenols, color intensity, etc. Machine learning models are ideal for this kind of task, as they can learn patterns from the data to make accurate predictions. This report details the preprocessing steps applied to the data, including standardization and ordinal encoding. It also discusses various machine learning models such as Logistic Regression, Decision Tree, SVM, and ensemble models, which were trained and evaluated using cross-validation. Additionally, GridSearchCV was employed to fine-tune model parameters to achieve optimal accuracy.

3. Methodology:

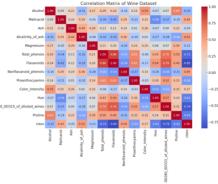
3.1 Dataset:

The Wine dataset used in this task contains 13 continuous features representing various chemical properties of wine, such as Alcohol, Malic acid, Ash, Magnesium, and Proline. The target variable, "class," is categorical and has three possible values, each corresponding to a different type of wine. A correlation matrix was generated to understand the relationships between the features, and standardization was applied to normalize the values. The dataset had no missing values.

3.2 Data Processing:

- Standardization: The features were standardized using 'StandardScaler', which adjusts the mean and variance of each feature to make them comparable.
 - Ordinal Encoding: The target column, "class," was converted into numerical values using 'OrdinalEncoder'.
- | |
|--|
| 0 1.518613 -0.582250 0.23 -1.169593 1.913905 0.808997 1.034819 -0.659563 1.224884 0.251717 0.36 1.847920 1.013 0 |
|--|

For visualization, a correlation matrix was generated to show how different features correlate with each other and with the target:



3.3 Modeling:

Several machine learning models were trained on the processed dataset using cross-validation for evaluation. The models include:

- **Logistic Regression:** A linear model suitable for binary and multiclass classification tasks.
- **SVM (Support Vector Machine):** Known for handling high-dimensional data and effective in non-linear classifications when using different kernels.
- **Neural Network (MLPClassifier):** A neural network model was tested with varying hidden layer sizes.
- **Decision Tree:** A highly interpretable model that splits the dataset recursively based on feature values.
- **Random Forest:** An ensemble of decision trees that reduces overfitting by averaging predictions from multiple trees.
- **Bagging:** An ensemble method that trains multiple classifiers on different subsets of the dataset.
- **Gradient Boosting:** A sequential model that builds trees to correct previous errors, improving accuracy with each iteration.
- **XGBoost:** A gradient boosting technique optimized for performance and speed.
- **AdaBoost:** An ensemble method that boosts weak classifiers by focusing more on incorrectly classified instances.

Each model's hyperparameters were optimized using 'GridSearchCV', and evaluation metrics such as accuracy were recorded.

4. Results:

The results of model evaluation are summarized below:

| Model | Best Parameters | Accuracy |
|---------------------|---|----------|
| Logistic Regression | Default | 0.9889 |
| SVM | {'C': 10, 'gamma': 'scale', 'kernel': 'rbf'} | 0.9889 |
| Neural Network | {'activation': 'tanh', 'alpha': 0.001, 'hidden_layer_sizes': (3, 4, 3)} | 0.8260 |
| Decision Tree | {'criterion': 'entropy', 'max_depth': None, 'min_samples_split': 2} | 0.9214 |
| Random Forest | {'max_depth': None, 'min_samples_split': 5, 'n_estimators': 500} | 0.9833 |
| Bagging | {'bootstrap': True, 'max_samples': 0.5, 'n_estimators': 100} | 0.9665 |
| GradientBoost | {'learning_rate': 1.0, 'max_depth': 3, 'n_estimators': 100} | 0.9665 |
| XGBoost | {'learning_rate': 0.1, 'max_depth': 3, 'n_estimators': 100} | 0.9554 |
| AdaBoost | {'algorithm': 'SAMME', 'learning_rate': 1.0, 'n_estimators': 10} | 0.9389 |

5. Conclusion:

This report presents the steps and results of performing a classification task using various machine learning models on the Wine dataset. Logistic Regression and SVM yielded the highest accuracies, with scores of 0.9889, demonstrating their effectiveness for this dataset. Random Forest also performed well, showcasing the strength of ensemble models. Neural Networks, while versatile, achieved a lower accuracy of 0.8260, indicating the need for further tuning. Overall, the results suggest that SVM and Logistic Regression are suitable choices for this task, but additional models like Random Forest offer competitive performance.

Figure S.15: A sample case of report generation.

G Experimental settings

Table S.6: The models and parameters used in the experiment.

| Experiment | Model | Parameters |
|--|---|------------------------------|
| Evaluation on ML datasets | Meta-Llama-3-8B-Instruct | temperature: 0.6, top-p: 0.9 |
| Reliability of function Calling method | Qwen1.5-7B-Chat, Qwen1.5-32B-Chat | temperature: 0.7, top-p: 0.8 |
| Generating evaluation dataset for function calling | Qwen1.5-110B | Not given |
| Generating evaluation dataset for LAMBDA | Qwen1.5-110B | Not given |
| Maximum number of APIs each LLM can process | Meta-Llama-3-8B-Instruct
Llama-2-7B-chat-hf
Qwen1.5-7B-Chat
Qwen-1-8B-Chat
chatglm3-6B
chatglm2-6B
Mistral-7B-Instruct-v0.2
Mistral-7B-Instruct-v0.1 | Not given |
| Comparative Study of Knowledge Integration | GPT-3.5-turbo-1106 and specific models | Not given |
| Case study of data analysis | GPT-3.5-turbo-1106 | Not given |
| Case study of integration human intelligence | Meta-Llama-3-8B-Instruct | temperature: 0.6, top-p: 0.9 |
| Case study of education | GPT-3.5-turbo-1106 | Not given |
| Case study of report generation | GPT-3.5-turbo-1106 | Not given |