DataPrep.EDA: Task-Centric Exploratory Data Analysis for Statistical Modeling in Python

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ABSTRACT

Exploratory Data Analysis (EDA) is a crucial step in any data science project. However, existing Python libraries fall short in supporting data scientists to complete common EDA tasks for statistical modeling. Their API design is either too low level, which is optimized for plotting rather than EDA, or too high level, which is hard to specify more fine-grained EDA tasks. In response, we propose DataPrep.EDA, a novel task-centric EDA system in Python. DataPrep.EDA allows data scientists to declaratively specify a wide range of EDA tasks in different granularity with a single function call. We identify a number of challenges to implement DataPrep.EDA, and propose effective solutions to improve the scalability, usability, customizability of the system. In particular, we discuss some lessons learned from using Dask to build the data processing pipelines for EDA tasks and describe our approaches to accelerate the pipelines. We conduct extensive experiments to compare DataPrep.EDA with Pandas-profiling, the state-of-the-art EDA system in Python. The experiments show that DataPrep.EDA significantly outperforms Pandas-profiling in terms of both speed and user experience. DataPrep.EDA is open-sourced as an EDA component of DataPrep: https://github.com/sfu-db/dataprep.

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1 INTRODUCTION

Python has grown to be one of the most popular programming languages in the world [33] and is widely adopted in the data science community. For example, the Python data science ecosystem, called PyData, is used by universities and online learning platforms to teach data science essentials [9, 16, 24, 34]. The ecosystem contains a wide range of tools such as Pandas for data manipulation and analysis, Matplotlib for data visualization, and Scikit-learn for machine learning, all aimed towards simplifying different stages of the data science pipeline.

Table 1: Comparison of EDA solutions in Python.

	Pandas+Plotting	Pandas-profiling	DataPrep.EDA
Easy to Use	×	✓	✓
Interactive Speed	✓	×	✓
Easy to Customize	✓	×	✓

In this paper we focus on one part of the pipeline, exploratory data analysis (EDA) for statistical modeling, the process of understanding data through data manipulation and visualization. It is an essential step in every data science project[72]. For statistical modeling, EDA often involves routine tasks such as understanding a single variable (univariate analysis), understanding the relationship between two random variables (bivariate analysis), and understanding the impact of missing values (missing value analysis).

Currently, there are two EDA solutions in Python. Each of them provide APIs in different granularity and have different drawbacks.

Pandas+Plotting. The first one is Pandas+Plotting, where Plotting represents a Python plotting library, such as Matplotlib [52], Seaborn [68], and Bokeh [42]. Fundamentally, plotting libraries are *not* designed for EDA but for plotting. Their APIs are at a very low level, hence they are not easy to use: To complete an EDA task, a data scientist needs to think about what plots to create, then using Pandas to manipulate the data so that it can be fed into a plotting library to create these plots. Often there is a gap between an EDA task and the available plots – a data scientist must write lengthy and repetitive code to bridge the gap.

Pandas-profiling. The second one is Pandas-profiling [43]. It provides a very high level API and allows a data scientist to generate a comprehensive profile report. The report has five main sections: `Overview`, `Variables`, `Interactions`, `Correlation`, and `Missing Values`. Its general utility makes it the most popular EDA library in Python. As of September, 2020, Pandas-profiling had over 2.5M downloads on PyPI and over 5.9K GitHub stars.

While Pandas-profiling is effective for one-time profiling, it suffers from two limitations for EDA due to its high-level API design: (i) Firstly, it does not achieve interactive speed since generating a profile report often takes a long time. This is suffering as EDA is an *iterative* process. Furthermore, the report shows information for all columns, potentially misdirecting the user and adding processing time. (ii) Secondly, it is not easy to customize a profile report. In a profile report, the plots are automatically generated thus it is very likely that the user wants to fine tune the parameters of each plot (e.g., the number of bins in a histogram). There could be hundreds of parameters associated with a profile report. It is not easy for users to figure out what they can customize and how to customize to meet their needs.

[*] Both authors contributed equally to this research.

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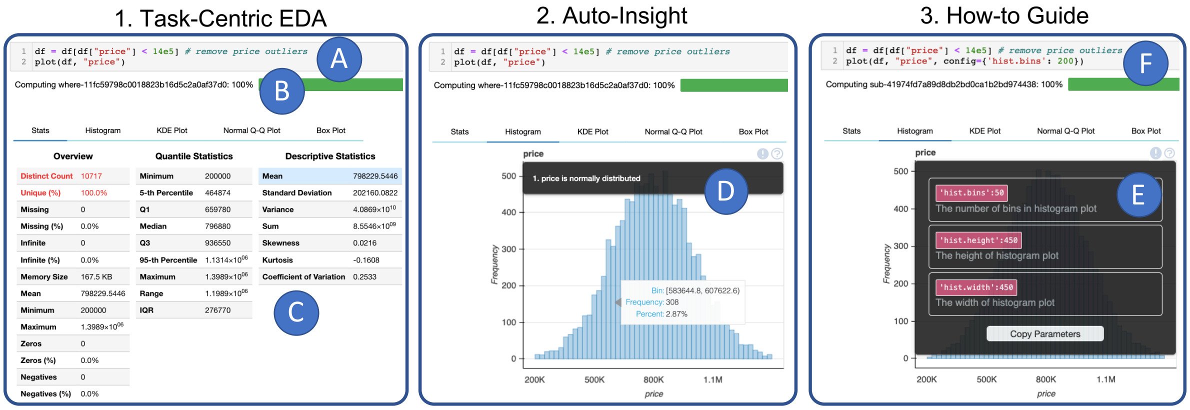


1. Task-Centric EDA

```
df = df[df["price"] < 14e5] # remove price outliers
plot(df, "price")
```

Computing where-11fc59798c0018823b16d5c2a0af37d0: 100%

Overview

Distinct Count	10717
Unique (%)	100.0%
Missing	0
Missing (%)	0.0%
Infinite	0
Infinite (%)	0.0%
Memory Size	167.5 KB
Mean	798229.5446
Minimum	200000
Maximum	1.3989×10^{06}
Zeros	0
Zeros (%)	0.0%
Negatives	0
Negatives (%)	0.0%

Quantile Statistics

Minimum	200000
5-th Percentile	464874
Q1	659780
Median	796880
Q3	936550
95-th Percentile	1.1314×10^{06}
Maximum	1.3989×10^{06}
Range	1.1989×10^{06}
IQR	276770

Descriptive Statistics

Mean	798229.5446
Standard Deviation	202160.0822
Variance	4.0869×10^{10}
Sum	8.5546×10^{09}
Skewness	0.0216
Kurtosis	-0.1608
Coefficient of Variation	0.2533

2. Auto-Insight

```
df = df[df["price"] < 14e5] # remove price outliers
plot(df, "price")
```

Computing where-11fc59798c0018823b16d5c2a0af37d0: 100%

1. price is normally distributed

Bin: [583644.8, 607622.6)
Frequency: 308
Percent: 2.87%

3. How-to Guide

```
df = df[df["price"] < 14e5] # remove price outliers
plot(df, "price", config={'hist.bins': 200})
```

Computing sub-41974fd7a89d8db2bd0ca1b2bd974438: 100%

'hist.bins':50
The number of bins in histogram plot

'hist.height':450
The height of histogram plot

'hist.width':450
The width of histogram plot

Figure 1: The front-end of DataPrep.EDA

Table 1 summarizes the drawbacks of Pandas+Plotting and Pandas-profiling. The key challenge is how to overcome the limitations of existing tools and design a new EDA system that can achieve three design goals: easy to use, with interactive speed, and easy to customize. To address this challenge, we build DataPrep.EDA, a novel task-centric EDA system in Python. We identify a list of common EDA tasks for statistical modeling, mapping each task to a single function call through careful API design. As a result of this task-oriented approach, DataPrep.EDA affords many more *fine-grained* tasks such as univariate analysis and correlation analysis. Figure 1-1 illustrates how our example user might use DataPrep.EDA to do a univariate analysis task after removing their outliers. The analyst calls the `plot`(df, "price") in DataPrep.EDA, where df is a dataframe and "price" is the column name. DataPrep.EDA detects `price` as a numerical variable and automatically generates suitable statistics (e.g., max, mean, quantile) and plots (e.g., histogram, box plot), which help the user gain a deeper understanding of the `price` column quickly and effectively.

With the task-centric approach, DataPrep.EDA is able to achieve all three design goals: (i) *Easy to Use.* Since each EDA task is directly mapped to a single function call, users only need to think about what tasks to work on rather than what to plot and how to plot. To further improve usability, we design an *auto-insight* component to automatically highlight possible interesting patterns in visualizations. (ii) *Interactive Speed.* Different from Pandas-profiling, DataPrep.EDA supports fine-grained tasks thus it can avoid unnecessary computation on irrelevant information. To further improve the speed, we carefully design our data processing pipeline based on Dask, a scalable computing framework in Python. (iii) *Easy to Customize.* With the task-centric API design, the parameters are grouped by different EDA tasks and each API only contains a small number of task-related parameters, making it much easier to customize. Besides, we implement a *how-to guide* component in DataPrep.EDA to further improve the customizability.

We conduct extensive experiments to compare DataPrep.EDA with Pandas-profiling. The performance results on 15 real-world datasets from Kaggle [19] show that i) DataPrep.EDA responded to a fine-grained EDA task in seconds while Pandas-profiling spent several orders of magnitude more time in creating a profile report on the same dataset; ii) if the task is to create a profile report, DataPrep.EDA was 4 − 20× faster than Pandas-profiling. Through a user study we show that i) real world participants of varying skill levels completed 2.05 times more tasks on average with DataPrep.EDA than with Pandas-profiling; ii) DataPrep.EDA helped participants answering 2.20 times more correct answers.

The following summarizes our contributions:

- We explore the limitations of existing EDA solutions in Python and propose a task-centric framework to overcome them.
- We design a task-centric EDA API for statistical modeling, allowing to declaratively specify an EDA task in one function call.
- We identify three challenges to implement DataPrep.EDA, and propose effective solutions to enhance the scalability, usability, and customizability of the system.
- We conduct extensive experiments to compare DataPrep.EDA with Pandas-profiling, the state-of-the-art EDA system in Python. The results show that DataPrep.EDA significantly outperforms Pandas-profiling in speed, effectiveness, and user preference.

2 RELATED WORK

EDA Tools in Python and R. Python and R are the two most popular programming languages in data science. Similar to Python, there are many EDA libraries in R including DataExplorer [10] and visdat [66] (see [64] for a recent survey). However, they are either similar to Pandas+Plotting or Pandas-profiling, thus having the same limitations as them. In the database community, recently, there is a growing interest in building EDA systems for Python programmers in order to benefit a large number of real-world data scientists [20, 48]. To the best our knowledge, DataPrep.EDA is the first task-centric EDA system in Python, and the only EDA system dedicated specifically to the notion of task-centric EDA.

GUI-based EDA. A GUI-based environment is commonly used for doing EDA, particularly among non-programmers. In such an environment, an EDA task is triggered by a click, drag, drop, etc (rather than a Python function call). Many commercial systems including Tableau [32], Excel [21], Spotfire [35], Qlik [25], Splunk [29], Alteryx [3], SAS [27], JMP [18] and SPSS [17] support doing EDA using a GUI. Although these systems are suitable in many cases, they all have the fundamental limitations of being removed from the programming environment and lacking flexibility.

In recent years, there has been abundant research in visualization recommendation systems [46, 49, 51, 55–57, 63, 70, 71]. Visualization recommendation is the process of automatically determining an interesting visualization and presenting it to the user. Another related area is automated insight generation (auto-insights). An auto-insight system mines a dataset for statistical properties of interest [22, 47, 50, 54, 65, 67]. Unlike these systems, DataPrep.EDA is a programming-based EDA tool that has several advantages over GUI-based EDA systems including seamless integration in the Python data science ecosystem, and flexibility since the data scientist is not restricted to one GUI's functionalities.

Data Profiling. Data profiling is the process of deriving summary information (e.g., data types, the number of unique values in columns) from a dataset (see [39] for a data profiling survey). Metanome [58] is a data profiling platform where the user can run profiling algorithms on their data to generate different summary information. Data profiling can be used in the tasks of data quality assessment (e.g., Profiler [53]) and data cleaning (e.g., Potter's Wheel [61]). Although DataPrep.EDA performs data profiling, unlike the above systems it is integrated effectively in a Python programming environment.

Python data profiling tools including Pandas-profiling [43], Sweetviz [31], and AutoViz [5], enable profiling a dataset by running one line of code. These systems provide rigid and coarse-grained analysis which are not suitable for general, ad-hoc EDA.

3 TASK-CENTRIC EDA

In this section, we first introduce common EDA tasks for statistical modeling, and then describe our task-centric EDA API design.

3.1 Common EDA Tasks for Statistical Modeling

Inspired by the profile report generated by Pandas-profiling and existing work [41, 59, 62], we identify five common EDA tasks. We will use a running example to illustrate why they are needed in the process of statistical modeling.

Suppose a data scientist wants to build a regression model to predict house prices. The training data consists of four features (`size`, `year_built`, `city`, and `house_type`) and the target (`price`).

- **Overview**. At the beginning, the data scientist has no idea about what's inside the dataset, so she wants to get a quick overview of the entire dataset. This involves computing some basic statistics and creating some simple visualizations. For example, she may want to check the number of features, the data type of each feature (numerical or categorical), and create a histogram for each numerical feature and a bar chart for each categorical feature.
- **Correlation Analysis**. To select important features or identify redundant features, correlation analysis is commonly used. It computes a correlation matrix, where each cell in the matrix represents the correlation between two columns. A correlation matrix can show which features are highly correlated with the target and which two features are highly correlated with each other. For example, if the feature, `size`, is highly correlated with the target, `price`, then knowing `size` will reveal a lot of information about `price`, thus it is an important feature. If two features, `city` and `house_type`, are highly correlated, then one of the features is redundant and can be removed
- **Missing Value Analysis**. It is more common than not for a dataset to have missing values. The data scientist needs to create customized visualizations to understand missing values. For example, she may create a bar chart, which depicts the amount of missing values in each column, or a missing spectrum plot, which visualizes which rows has more missing values.
- **Univariate Analysis**. Univariate analysis aims to gain a deeper understanding of a single column. It creates various statistics and visualizations of that column. For example, to deeply understand the feature `year_built`, the data scientist may want to compute the min, max, distinct count, median, variance of `year_built`, and create a box plot to examine outliers, a normal Q-Q plot to compare its distribution with the normal distribution.
- **Bivariate Analysis**. Bivariate analysis is to understand the relationship between two columns (e.g., a feature and the target). There are many visualizations to facilitate the understanding. For example, to understand the relationship between `year_built` and `price`, she may want to create a scatter plot to check whether they have a linear relationship, and a hexbin plot to check the distribution of `price` in different year ranges.

There are certainly other EDA tasks used for statistical modeling, however we have opted to focus on the main tasks systems such as Pandas-profiling commonly present in their reports. This allows us to make a fair comparison between our system design approaches. In the future we intend to address more tasks, such as time-series analysis and multi-variate analysis (more than two variables).

3.2 DataPrep.EDA's Task-Centric API Design

The goal of our API design is to enable the user to trigger an EDA task through a single function call. We consider simplicity and consistency as the principle of API design. The simple and consistent API makes our system more accessible in practice [44]. However, it is challenging to design simple and consistent APIs for a variety of EDA tasks. Our key observation is that the EDA tasks for statistical modeling tend to follow a similar pattern [69]: start with an overview analysis and then dive into detailed analysis. Hence, we design the API in the following form:

plot_*tasktype*(df, col_list, config),

where plot_*tasktype* is the function name, tasktype is a concise description of the task, the first argument is a DataFrame, the second argument is a list of column names, and the third argument is a dictionary of configuration parameters. If column names are not specified, the task will be performed on all the columns in the DataFrame (overview analysis); otherwise, it will be performed on the specified column(s) (detailed analysis). This design makes the API extensible, i.e., it is easy to add an API for a new task.

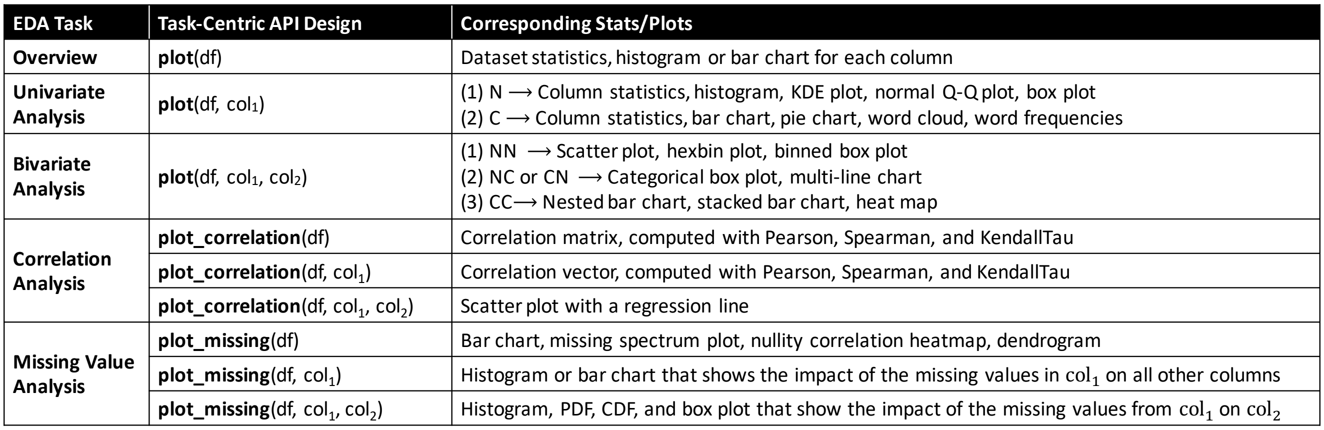
Following this pattern, we design three functions in DataPrep.EDA to support the five EDA tasks:

plot. We use the `plot(·)` function with different arguments to represent the overview task, the univariate analysis task, and the bivariate analysis task, respectively. To understand how to perform EDA effectively with this function, the following gives the syntax of the function call with the intent of the data scientist:

- plot(df): "I want an overview of the dataset"
- plot(df, $\texttt{col}_1$): "I want to understand $\texttt{col}_1$"
- plot(df, $\texttt{col}_1$, $\texttt{col}_2$): "I want to understand the relationship between $\texttt{col}_1$ and $\texttt{col}_2$"

plot_correlation. The `plot_correlation(·)` function triggers the correlation analysis task. The user can get more detailed correlation analysis results by calling `plot_correlation`(df, col_1) or `plot_correlation`(df, col_1, col_2).

- plot_correlation(df): "I want an overview of the correlation analysis result of the dataset"
- plot_correlation(df, $\texttt{col}_1$): "I want to understand the correlation between $\texttt{col}_1$ and the other columns"



EDA Task	Task-Centric API Design	Corresponding Stats/Plots
Overview	**plot**(df)	Dataset statistics, histogram or bar chart for each column
Univariate Analysis	**plot**(df, col$_1$)	(1) N ⟶ Column statistics, histogram, KDE plot, normal Q-Q plot, box plot (2) C ⟶ Column statistics, bar chart, pie chart, word cloud, word frequencies
Bivariate Analysis	**plot**(df, col$_1$, col$_2$)	(1) NN ⟶ Scatter plot, hexbin plot, binned box plot (2) NC or CN ⟶ Categorical box plot, multi-line chart (3) CC⟶ Nested bar chart, stacked bar chart, heat map
Correlation Analysis	**plot_correlation**(df)	Correlation matrix, computed with Pearson, Spearman, and KendallTau
	plot_correlation(df, col$_1$)	Correlation vector, computed with Pearson, Spearman, and KendallTau
	plot_correlation(df, col$_1$, col$_2$)	Scatter plot with a regression line
Missing Value Analysis	**plot_missing**(df)	Bar chart, missing spectrum plot, nullity correlation heatmap, dendrogram
	plot_missing(df, col$_1$)	Histogram or bar chart that shows the impact of the missing values in col$_1$ on all other columns
	plot_missing(df, col$_1$, col$_2$)	Histogram, PDF, CDF, and box plot that show the impact of the missing values from col$_1$ on col$_2$

Figure 2: A set of mapping rules between EDA tasks and corresponding stats/plots (N = Numerical, C = Categorical)

- plot_correlation(df, col$_1$, col$_2$): "I want to understand the correlation between col$_1$ and col$_2$"

plot_missing. The plot_missing(·) function triggers the missing value analysis task. Similar to plot_correlation(·), the user can call plot_missing(df, col$_1$) or plot_missing(df, col$_1$, col$_2$) to get more detailed analysis results.

- plot_missing(df): "I want an overview of the missing value analysis result of the dataset"
- plot_missing(df, col$_1$): "I want to understand the impact of removing the missing values from col$_1$ on other columns"
- plot_missing(df, col$_1$, col$_2$): "I want to understand the impact of removing the missing values from col$_1$ on col$_2$"

The key observation that makes task-centric EDA possible is that there are nearly universal kinds of stats or plots that analysts employ in a given EDA task. For example, if the user wants to perform univariate analysis on a numerical column, she will create a histogram to check the distribution, a box plot to check the outliers, a normal Q-Q plot to compare with the normal distribution, etc. Based on this observation, we pre-define a set of mapping rules as shown in Figure 2, where each rule defines what stats/plots to create for each EDA task. Once a function, e.g., plot(df,"price"), is called, DataPrep.EDA first detects the data type of price, which is numerical. Based on the second row in Figure 2, since col$_1$ = N, DataPrep.EDA will automatically generate the column statistics, histogram, KDE plot, normal Q-Q plot, and box plot of price.

The mapping rules are selected from existing literature and open-source tools in the statistics and machine learning community. For univariate, bivariate, and correlation analysis, we refer to the data-to-viz project [13], 'Exploratory Graphs' section in [59] and Section 4 in [62]. For overview analysis and missing value analysis, the mapping rules are derived from the Pandas-profiling library and the Missingno library [41], respectively. DataPrep.EDA also leverages the open-source community to keep adding and improving its rules. For example, one user has created an issue in our GitHub repository to suggest adding violin plots to the plot(df,x) function. As DataPrep.EDA is being used by more users, we expect to see more suggestions like this in the future.

4 SYSTEM ARCHITECTURE

This section describes DataPrep.EDA's front-end user experience and introduces the back-end system architecture.

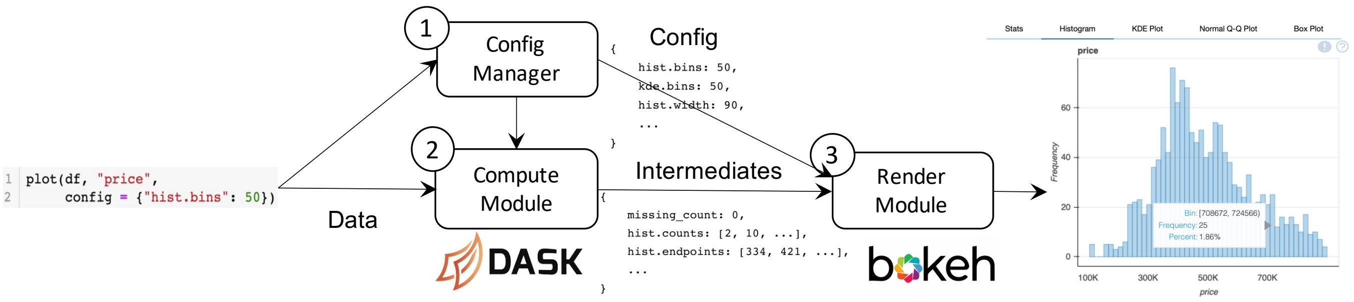
4.1 Front-end User Experience

To demonstrate DataPrep.EDA, we will continue our house price prediction example, using DataPrep.EDA to assist in removing outliers from the price variable, assessing the resulting distribution, and determining how to further customize the analysis. Figure 1 depicts the steps to perform this task using Pandas and DataPrep.EDA in a Jupyter notebook. Part Ⓐ shows the required code: in line 1, the records with an outlying price value are removed (the threshold is $1,400,000), and in line 2 the DataPrep.EDA function plot is called to analyze the filtered distribution of the variable price. Part Ⓑ shows the progress bar. Part Ⓒ shows the default output tab which consists of tables containing various statistics of the column's distribution. Note that each data visualization is output in a separate panel, and tabs are used to navigate between panels.

- **Auto-Insight**. If an insight is discovered by DataPrep.EDA, a (❗) icon will be shown on the top right corner of the associated plot. Part Ⓓ shows an insight associated with the histogram plot: price is normally distributed.
- **How-to Guide**. A how-to guide will pop up after clicking a (❓) icon. As shown in Part Ⓔ, it contains the information about customizing the associated plot. In this example, the data scientist may want to create a histogram with more bins, so she can copy the code ("hist.bins":50) in the how-to guide, paste it as a parameter to the plot function, and increase the number of bins from 50 to 200 as shown in Part Ⓕ.

4.2 Back-end System Architecture

The DataPrep.EDA back-end is presented in Figure 3, consisting of three components: ① The Config Manager configures the system's parameters, ② the Compute module performs the computations on the data, and ③ the Render module creates the visualizations and layouts. The Config Manager is used to organize the user-defined parameters and set default parameters in order to avoid setting and passing many parameters through the Compute and Render modules. The separation of the Compute module and the Render module has two benefits: First, the computations can be distributed to multiple visualizations. For example, in plot(df, col$_1$=N) in Figure 2, the column statistics, normal Q-Q plot, and box plot all require quantiles of the distribution. Therefore, the quantiles are computed once and distributed appropriately to each visualization. Second, the intermediate computations (see Section 4.2.2) can be



```
plot(df, "price",
     config = {"hist.bins": 50})
```

```
{
  hist.bins: 50,
  kde.bins: 50,
  hist.width: 90,
  ...
}
```

```
{
  missing_count: 0,
  hist.counts: [2, 10, ...],
  hist.endpoints: [334, 421, ...],
  ...
}
```

Figure 3: The DataPrep.EDA system architecture

exposed to the user. This allows the user to create the visualizations with her desired plotting library.

4.2.1 Config Manager. The Config Manager (① in Figure 3) sets values for all configurable parameters in DataPrep.EDA, and stores them in a data structure, called the `config`, which is passed through the rest of the system. Many components of DataPrep.EDA are configurable including which visualizations to produce, the insight thresholds (see Section 4.2.2), and visualization customizations such as the size of the figures. In Figure 3, the `plot` function is called with the user specification `bins=50`; the Config Manager sets each bin parameter to have a value of 50, and default values are set for parameters not specified by the user. The `config` is then passed to the Compute and Render modules and referenced when needed.

4.2.2 Compute module. The Compute module takes the data and `config` as input, and computes the `intermediates`. The `intermediates` are the results of all the computations on the data that are required to generate the visualizations for the EDA task. Figure 3 shows example `intermediates`. The first element is the count of missing values which is shown in the `Stats` tab, and the next two elements are the counts and bin endpoints of the histogram. Such statistics are ready to be fed into a visualization.

Insights are calculated in the Compute module. A data fact is classified as an insight if its value is above a threshold (each insight has its own, user-definable threshold). For example, in Figure 1 (Part Ⓑ), the distinct value count is high, so the entry in the table is highlighted red to alert the user about this insight. DataPrep.EDA supports a variety of insights including data quality insights (e.g., missing, infinite values), distribution shape insights (e.g., uniformity, skewness) and whether two distributions are similar.

We developed two optimization techniques to increase performance. First, we share computations between multiple visualizations as described in the beginning of Section 4.2. Second, we leverage Dask to parallelize computations (see Section 5 for details).

4.2.3 Render module. The last system component is the Render module, which converts the `intermediates` into data visualizations. There is a plethora of Python plotting libraries (e.g., Matplotlib, Seaborn, and Bokeh), however, they provide limited or no support for customizing a plot's *layout*. A *layout* is the surrounding environment in which visualizations are organized and embedded. Our layouts need to consolidate many elements including charts, tables, insights, and how-to guides. To meet our needs, we use the library Bokeh to create the plots, and embed them in our own HTML/JS layout.

5 IMPLEMENTATION

In this section, we introduce the detailed implementation of DataPrep.EDA's Compute module. We first introduce the background of Dask and discuss why we choose Dask as the back-end engine. We then present our ideas for using Dask to optimize DataPrep.EDA.

5.1 Why Dask

Dask Background. Dask is an open source library providing scalable analytics in Python. It offers similar APIs and data structures with other popular Python libraries, such as NumPy, Pandas, and Scikit-Learn. Internally, it partitions data into chunks, and runs computations over chunks in parallel.

The computations in Dask are lazy. Dask will first construct a computational graph that expresses the relationship between tasks. Then, it optimizes the graph to reduce computations such as removing unnecessary operators. Finally, it executes the graph when an eager operation like `compute` is called.

Choice of Back-end Engine. We use Dask as the back-end engine of DataPrep.EDA for three reasons: (i) it is lightweight and fast in a single-node environment, (ii) it can scale to a distributed cluster, and (iii) it can optimize the computations required for multiple visualizations via lazy evaluation. We considered other engines like Spark variants [38, 73] (PySpark and Koalas) and Modin [60], but found that they were less suitable for DataPrep.EDA than Dask. Since Spark is designed for computations on very big data (TB to PB) in a large cluster, PySpark and Koalas are not lightweight like Dask and have a high scheduling overhead on a single node. For Modin, most of its operations are eager, so for each operation a separate computational graph is created. This approach does not optimize across operations, unlike Dask's approach. In Section 6.2, we further justify our choice to use Dask experimentally.

5.2 Performance Optimization

Given an EDA task, e.g., `plot_missing(df)`, we discuss how to efficiently compute its `intermediates` using Dask. We observe that there are many redundant computations between visualizations. For example, as shown in Figure 2, `plot_missing(df)` creates four visualizations (bar chart, missing spectrum plot, nullity correlation heatmap, and dendrogram). They share many computations, such as computing the number of rows, checking whether a cell is missing or not. To leverage Dask to remove redundant computations, we seek to express all the computations in a *single* computational graph. To implement this idea, we can make all the computations lazy and call an eager operation at the end. In this way, Dask will optimize the whole graph before actual computations happen.

However, there are several issues with this implementation. In the following, we will discuss them and propose our solutions.

Dask graph fails to build. The first issue is that the `rechunk` function in Dask cannot be directly incorporated into the big computational graph. This is because that its first argument, a Dask

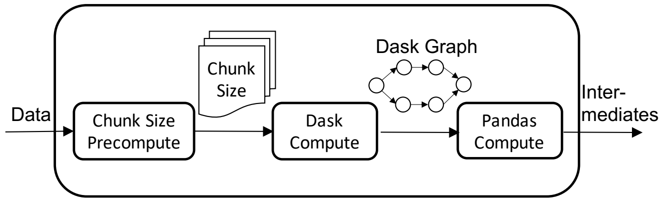


Figure 4: Data processing pipeline in the Compute module

array, requires knowing the chunk size information, i.e., the size of each chunk in each dimension. If rechunk was put into our computational graph, an error would be raised since the chunk size information is unknown for a delayed Dask array.

Since rechunk is needed in multiple plot functions in DataPrep.EDA, we have to address this issue. One solution is to replace the rechunk function call in each plot function with the code written by the low-level Dask task graph API. However, this solution has a high engineering cost, which requires writing hundreds of lines of Dask code. It also has a high maintenance cost compared to using the Dask built-in rechunk function.

We propose to add an additional stage before constructing the computational graph. In this stage, we precompute the chunk size information of the dataset and pass the precomputed chunk size to the Dask graph. In this way, the Dask graph can be constructed successfully by adding one line of code.

Dask is slow on tiny data. Although putting all possible operations in the graph can fully leverage Dask's optimizations, it also increases the overhead caused by scheduling. When data is large, the scheduling overhead is negligible compared to the computing overhead. However, when data is tiny, the scheduling may be the bottleneck and using Dask is less efficient than using Pandas.

For the nine plot functions in Figure 2, we observe that they all follow the same pattern: the computational graph takes as input a DataFrame (large data) and continuously reduces its size by aggregation, filtering, etc. Based on this observation, we separate the computational graph into two parts: *Dask Computation* and *Pandas Computation*. In the *Dask Computation*, the data is computed in Dask and the result is transformed into a Pandas DataFrame. In the *Pandas Computation*, it takes the DataFrame as input and does some further processing to generate the intermediate results, which will be used to create visualizations.

Currently, we heuristically determine the boundary between the two parts. For example, the computation for plot_correlation(df) is separated into two stages. In the first stage we use Dask to compute the correlation matrix from the user input and then in the second stage we use Pandas to transform and filter the correlation matrix. This is because for a dataset with n rows and m columns, it is usually the case that $n >> m$. As a result, it would be beneficial to let Pandas handle the correlation matrix, which has the size $m \times m$. Since we only need to handle nine plot functions, it is still manageable. We will investigate how to automatically separate the two parts in the future.

Putting everything together. Figure 4 shows the data processing pipeline in the Compute module of DataPrep.EDA. When data comes, DataPrep.EDA first precomputes the chunk size information using Dask. After that, it constructs the computational graph using Dask again with the precomputed chunk size filled. Then, it computes the graph. After that, it transforms the computed data into Pandas and finishes the Pandas computation. In the end, the intermediates are returned.

Table 2: Comparing DataPrep.EDA with Pandas-profiling on 15 real-world data science datasets from Kaggle (N = Numerical, C = Categorical, PP=Pandas-profiling).

Dataset	Size	#Rows	#Cols (N/C)	PP	DataPrep	Faster
heart [14]	11KB	303	14 (14/0)	17.7s	2.0s	8.6×
diabetes [23]	23KB	768	9 (9/0)	28.3s	1.6s	17.7×
automobile [4]	26KB	205	26 (10/16)	38.2s	3.9s	9.8×
titanic [36]	64KB	891	12 (7/5)	17.8s	2.1s	8.5×
women [37]	500KB	8553	10 (5/5)	19.8s	2.3s	8.6×
credit [11]	2.7MB	30K	25 (25/0)	127.0s	6.1s	20.8×
solar [28]	2.8MB	33K	11 (7/4)	25.1s	2.7s	9.3×
suicide [30]	2.8MB	28K	12 (6/6)	20.6s	2.8s	7.4×
diamonds [12]	3MB	54K	11 (8/3)	28.2s	3.1s	9×
chess [8]	7.3MB	20K	16 (6/10)	23.6s	4.3s	5.5×
adult [2]	5.7MB	49K	15 (6/9)	23.2s	4.0s	5.8×
basketball [6]	9.2MB	53K	31 (21/10)	126.2s	9.9s	12.7×
conflicts [1]	13MB	34K	25 (10/15)	34.9s	8.6s	4×
rain [26]	13.5MB	142K	24 (17/7)	100.1s	11.6s	8.6×
hotel [15]	16MB	119K	32 (20/12)	83.2s	13s	6.4×

6 EXPERIMENTAL EVALUATION

In this section, we conduct extensive experiments to evaluate the efficiency and the user experience of DataPrep.EDA.

6.1 Performance Evaluation

We first evaluate the performance of DataPrep.EDA by comparing its report functionality with Pandas-profiling. Afterwards, we conduct a self comparison, which evaluates each plot function with different variations, in order to gain a deep understanding of the performance. We used 15 different datasets varying in number of rows, number of columns and categorical/numerical column ratio, as listed in Table 2. The experiments were performed on an Ubuntu 16.04 Linux server with 64 GB memory and 8 Intel E7-4830 cores.

Comparing with Pandas-profiling. To test the general efficiency of DataPrep.EDA, we compared the end-to-end running time of generating reports over the 15 datasets in both tools. For Pandas-profiling, we first used read_csv from Pandas to read the data, then we created a report in Pandas-profiling with PhiK, Recoded and Cramer's V correlations disabled (since DataPrep.EDA does not implement these correlation types). For DataPrep.EDA, we used read_csv from Dask to read the dataset. Since it is a one-time task to create a profiling report, loading the data using the most suitable function for each tool is reasonable. Results are shown in Table 2. We observe that using DataPrep.EDA to generate reports is 4x ∼ 20x faster compared to Pandas-profiling in general. The acceleration mainly comes from the optimization to make the tasks into a single Dask graph so that they can be fully parallelized. We also observe that DataPrep.EDA usually gains more performance compared to Pandas-profiling on numerical data and data with fewer categorical columns (driving performance on credit, basketball, and diabetes).

Self-comparison. We analyzed the running time of DataPrep.EDA's functions to determine whether they can complete within a reasonable response time for interactivity. We ran plot(), plot_correlation(), and plot_missing() for each column in each dataset, and we ran the three functions for all unique pairs of columns in each dataset (limited to categorical columns with no more than 100 unique values for plot(df, $\texttt{col}_1$, $\texttt{col}_2$) so the resulting visualizations contain a reasonable amount of information).

Figure 5 shows the percent of total tasks for each function that finish within 0.5, 1, 2 and 5 seconds. Note that dataset loading time is also included in the reported run times. The majority of tasks completed within 1 second for each function except plot_missing(df, col$_1$). plot_missing(df, col$_1$) is computationally intensive because it computes two frequency distributions for each column (before and after dropping the missing values in column col$_1$).

6.2 Experiments on Large Data

We conduct experiments to justify the choice of Dask (see Section 5.1) and evaluate the scalability of DataPrep.EDA. We use the bitcoin dataset [7] which contains 4.7 million rows and 8 columns.

Comparing Engines. We compare the time required for Dask, Modin, Koalas, and PySpark to compute the intermediates of plot(df). The results are shown in Figure 6(a). The reason why Dask is the fastest is explained in Section 5.1: Modin eagerly evaluates the computations and does not make full use of parallelization when computing multiple visualizations, and Koalas/PySpark have a high scheduling overhead in a single-node environment.

Varying Data Size. To evaluate the scalability of DataPrep.EDA, we compare the report functionality of DataPrep.EDA with Pandas-profiling and vary the data size from 10 million to 100 million rows. The data size is increased by repeated duplication. The results are shown in Figure 6(b). Both DataPrep.EDA and Pandas-profiling scale linearly, but DataPrep.EDA is around six times faster. This is because DataPrep.EDA leverages lazy evaluation to express all the computations in a single computational graph so that the computations can be fully parallelized by Dask.

Varying # of Nodes. To evaluate the performance of DataPrep.EDA in a cluster environment, we run the report functionality on a cluster and vary the number of nodes. The cluster consists of a maximum of 8 nodes, each with 64GB of memory and 16 2.0GHz E7-4830 CPUs dedicated to the Dask workers. There are also HDFS services running on the 8 nodes for data storage; the memory for these services is not shared with the Dask workers. The data is fixed at 100 million rows and stored in HDFS. We do not compare with Pandas-profiling since it cannot run on a cluster. The result is shown in Figure 6(c). We can see that DataPrep.EDA is able to run on a cluster and achieves better performance as increasing the number of nodes. This is because adding more compute nodes can reduce the I/O cost of reading data from HDFS. It is worth noting that the 1 worker setting in Figure 6(c) is different from the single node setting in Figure 6(b) where the former needs to read data from HDFS while the latter reads data from a local disk. Therefore, the 1 worker setting took longer to process 100 million rows than the single node setting.

6.3 User Study

Finally, we conducted a user study to validate the usability of our tool and its utility in supporting analytics. We focus on two questions using Pandas-profiling as a comparison baseline: (1) For different groups of participants, how do they benefit from the task-centric features introduced by DataPrep.EDA, and (2) Does DataPrep.EDA reduce participants’ false discovery rate. We hypothesize that the intuitive API in DataPrep.EDA will lead participants to complete more tasks in less time versus Pandas-profiling, and that the additional tools provided by DataPrep.EDA will help participants to reduce their false discovery rate.

Methodology. In our study, all recruited participants used both DataPrep.EDA and Pandas-profiling to complete two different sets of tasks in a 50 minute session with software logging: one tool is used for one set of tasks. Afterwards, they assessed both systems in surveys. Our study employs two datasets paired with task sets: (1) BirdStrike: 12 columns related to bird strike damage on airplanes. The dataset compiles approximately 220, 000 strike reports from 2, 050 USA airports and 310 foreign airports. (2) DelayedFlights: 14 columns related to the causes of flight cancellations or delays. The dataset is curated by the Department of Transportation of United States, and contains 5, 819, 079 records of cancelled flights.

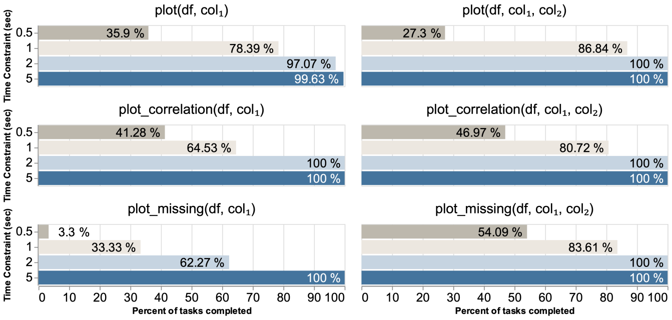


Figure 5: The percentage of tasks to finish within the given time constraint.

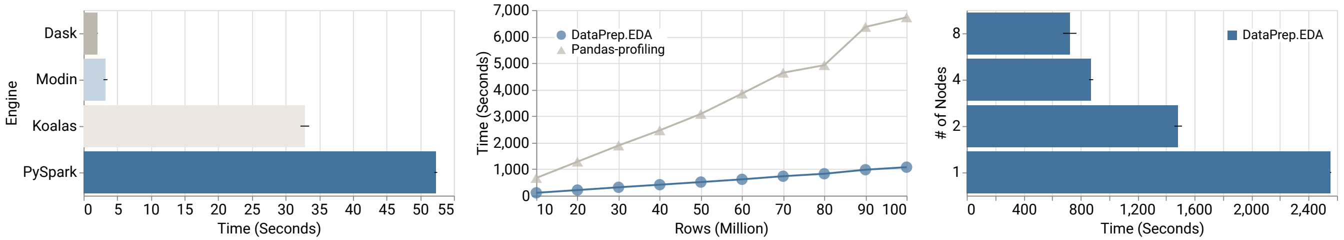
We followed a within-subjects design, with all participants making use of either tool to complete one set of tasks. We counterbalanced our allocation to account for all tool-dataset permutations and order effects. Within each task, participants finished five sequential tasks using one tool. As experience might influence how much an individual benefits from each tool, we recruited both skilled and novice analysts using a pre-screen concerning knowledge of python, data analysis, and the datasets in the study. To make sure that all participants had base knowledge of how to use both Pandas-profiling and DataPrep.EDA, we gave participants with two introductory videos, a cheat sheet, and API documentation.

Participants were asked to complete 5 tasks sequentially using the data analysis tool. The tasks are designed to evaluate different functions provided by DataPrep.EDA, which is similar to the design of existing work [40]. They cover a relatively wide spectrum of the kinds of tasks that are frequently encountered in EDA, including gathering descriptive multivariate statistics of one or multiple columns, identifying missing values, and finding correlations. Though datasets have their own specific task instructions, each of the respective items shares the same goal across both datasets. For example, the first task of both sessions asks participants to investigate data distribution over multiple columns.

In Task 1-3, participants use the provided tool to analyze the distribution of single or multiple columns. Participants conduct a univariate analysis in task 1 and a variate analysis in task 2. The task 3 asked the participant to examine distribution skewness. Task 4 examines missing values and their impact. Participants are expected to examine the distribution of missing values to come to a conclusion. Task 5 asks users to find columns with high correlation.

We use the fraction $\frac{\#correctanswers}{\#completedtasks}$ to show the *relative accuracy* of participants, since we noticed that a number of participants failed to finish tasks. Compared to traditional accuracy, relative accuracy therefore may better demonstrate positive discovery rate [45].

Examining Participants’ Performance. We examine accuracy and completed tasks to evaluate system performance. The average



(a) Comparing Engines (Single Node) (b) Varying Data Size (Single Node) (c) Varying # of Nodes

Figure 6: Experiments on the Bitcoin Dataset: (a) Comparing the running time of using different engines to compute visualizations in plot(df); (b) Comparing the running time of create_report(df) of DataPrep.EDA and Pandas-profiling by varying data size; (c) Evaluating the running time of create_report(df) of DataPrep.EDA by varying the number of nodes.

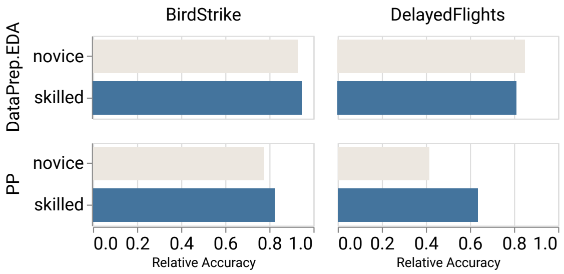


Figure 7: Relative Accuracy of DataPrep.EDA and Pandas-profiling across different skill levels of participants in dataset BirdStrike and DelayedFlights.

number of completed tasks per participant using DataPrep.EDA (M:4.02, SD:1.21) was ***2.05*** times higher than that using Pandas-profiling (M:1.96, SD: 2.59, t(29)=5.26, $\rho < .00001$). When we compared skill levels, we could detect no difference (t(14)=.882998, $\rho < .441499$). Together, this suggests that DataPrep.EDA generally improved participants’ efficiency in performing EDA tasks. Factoring in dataset, we find that Pandas-profiling performs better in small datasets(M:3, SD:4.13) compared to a more complex one (M:1.1, SD:1.20, t(14)=−3.26062, $\rho < .0028$). As dataset complexity grows, Pandas-profiling fails to scale up. No participants finished all tasks, and 42% finished at most one task using Pandas-profiling. On the other hand, 35% of DataPrep.EDA participants finished all five tasks for the *delayed* dataset. We did not observe a dataset difference for DataPrep.EDA (t(14)=−0.66, $\rho < .51$), which suggests that it scaled well and might have pushed participants towards an efficiency ceiling.

In terms of the number of correct answers versus ground truth, participants who used DataPrep.EDA (M:3.72, SD:0.06) were ***2.2*** times more accurate compared to those using Pandas-profiling (M:1.70, SD:3.56, t(29)=2.791, $\rho < .001$), which suggests that DataPrep.EDA better assisted users in analyzing and reduced the risk of false discoveries. We again found that there was no significant difference detected between datasets (t(14)=.4156, $\rho < .1299$), however, as in completed tasks, we find that Pandas-profiling did a significantly better job for small datasets and failed to guide users for larger ones (t(14)=−1.27, $\rho < .00042$). These results are encouraging: DataPrep.EDA can help participants with different skill-levels complete many tasks with fewer errors.

As the number of completed tasks affects the amount of (in)correct answers, we used our relative accuracy metric. The average relative accuracy of DataPrep.EDA (M: .82 , SD: 0.07) among participants was ***1.5*** times higher than Pandas-profiling (M: .53 , SD: 1.35). Considering expertise and dataset complexity (Figure 7), we find that users from both skill levels achieve similar relative accuracy in both datasets, but skilled participants did significantly better than novice participants only for Pandas-profiling in complex datasets. This suggests that DataPrep.EDA performed better at leveling skill differences and dataset complexity.

Qualitative feedback. In our post-survey we also asked participants to share comments and feedback to add context to the performance differences we observed. In our quantitative results, participants often referenced the responsiveness and efficiency of DataPrep.EDA (“fast and responsive”) and took issue with the speed of Pandas-profiling (“it didn’t work, took forever to process”, "I would also like to use Pandas-profiling if the efficiency is not the bottleneck"). We also asked how more granular information affected their performance. Participants reflected that they felt more control (“I can find the necessary information very quickly, and that really helps a lot for me to solve the problems and questions very quickly", “felt like I had more control, simpler results”) and accessible (“I find all the answers I need, and DataPrep.EDA is more easy to understand”).

7 CONCLUSION & FUTURE WORK

In this paper, we proposed a task-centric EDA tool design pattern and built such a system in Python, called DataPrep.EDA. We carefully designed the API in DataPrep.EDA, mapping common EDA tasks in statistical modeling to corresponding stats/plots. Additionally, DataPrep.EDA provides tools for automatically generating insights and providing guides. Through our implementation, we discussed several issues in building data processing pipelines using Dask and presented our solutions. We conducted a performance evaluation on 15 real-world data science datasets from Kaggle and a user study with 32 participants. The results showed that DataPrep.EDA significantly outperformed Pandas-profiling in terms of both speed and user experience.

We believe that task-centric EDA is a promising research direction. There are many interesting research problems to explore in the future. Firstly, there are some other EDA tasks for statistical modeling. For example, time-series analysis is a common EDA task in finance (e.g., stock price analysis). It would be interesting to study how to design a task-centric API for these tasks as well. Secondly, we notice that the speedup of DataPrep.EDA over Pandas tends to get small when IO becomes the bottleneck. We plan to investigate how to reduce IO cost using data compression techniques and column store. Thirdly, we plan to leverage sampling and sketches to speed up computation. The challenges are i) how to detect the scenarios of applying sampling/sketches; ii) how to notify users of the possible risk of sampling/sketches in a user-friendly way.

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