Goals, Process, and Challenges of Exploratory Data Analysis: An Interview Study

Kanit Wongsuphasawat*  Yang Liu†  Jeffrey Heer‡

Apple Inc.  University of Washington  University of Washington

ABSTRACT

How do analysis goals and context affect exploratory data analysis (EDA)? To investigate this question, we conducted semi-structured interviews with 18 data analysts. We characterize common exploration goals: profiling (assessing data quality) and discovery (gaining new insights). Though the EDA literature primarily emphasizes discovery, we observe that discovery only reliably occurs in the context of open-ended analyses, whereas all participants engage in profiling across all of their analyses. We describe the process and challenges of EDA highlighted by our interviews. We find that analysts must perform repetitive tasks (e.g., examine numerous variables), yet they may have limited time or lack domain knowledge to explore data. Analysts also often have to consult other stakeholders and oscillate between exploration and other tasks, such as acquiring and wrangling additional data. Based on these observations, we identify design opportunities for exploratory analysis tools, such as augmenting exploration with automation and guidance.

Index Terms: Human-centered computing—Visualization—Visualization techniques—Treemaps; Human-centered computing—Visualization—Visualization design and evaluation methods

1 INTRODUCTION

Exploratory data analysis (EDA), as introduced by Tukey [67], aims to complement formal confirmatory analysis with a "flexible attitude", letting data exposure inform analysts’ modeling decisions [55]. With this attitude, analysts usually “explore” aspects of data by examining data values, derived statistics, and visualizations. Today, data exploration is widely adopted as a critical part of data science, both in industrial and scientific settings [35]. However, while analysts perform data exploration in various kinds of analyses, the EDA literature lacks a consistent definition of exploration goals. Moreover, little research has observed how analysis goals and context affect the day-to-day practice and challenges of EDA. Understanding these issues can inform the design of data exploration tools.

To better understand current EDA practices, we conducted semi-structured interviews with 18 analysts from academic and industrial settings. We asked the analysts to describe their analysis goals, tasks they performed, and challenges they faced in their exploration. We first describe observed analysis context and process. We discuss observed types of analyses that involve exploration and identify two common exploration goals: profiling (understanding what the data contain and assessing data quality) and discovery (gaining new insights). Though the EDA literature emphasizes discovery, we observe that all participants engage in profiling across all of their analyses, while discovery only reliably occurs in open-ended analyses, which participants perform less often. Based on the participants’ descriptions of their analysis process, we revise Kandel et al.’s model of the data analysis process [42] to include exploration. We also report the analysts’ context including tools, domain knowledge (or the lack thereof), and involved stakeholders.

Next, we discuss recurring observed challenges in the data analysis process and report how analysis goals and context impact them. We also describe how analysts handle challenges specific to exploration tasks including choosing variables to explore, handling repetitive tasks, and determining the end of an exploration. We find that analysts often have to explore numerous variable combinations, requiring them to apply domain knowledge to select and reduce the number of variables. As analysts perform repetitive tasks, they may curate analysis templates to automate their routines and help them follow best practices. Due to time limits, analysts may also need to move on to other tasks before completing their exploration.

Finally, we identify opportunities for data exploration tools. We argue that tools can help mitigate these observed challenges and facilitate rapid and systematic exploration by providing automation for routine tasks and guiding analysis practices. We also note a lack of support for data wrangling and navigation of analysis history within exploration tools.

2 BACKGROUND AND RELATED WORK

We build on the exploratory data analysis literature and complement prior work on understanding data analysis.

2.1 Exploratory Data Analysis

Exploratory data analysis stems from the collection of work by the statistician John Tukey in the 1960s and 1970s [24, 39, 40, 67]. His seminal book [67] compiles a collection of data visualization techniques as well as robust and non-parametric statistics for data exploration. Many communities including Statistics, Human-Computer Interaction, and Information Visualization have since contributed new data exploration tools and techniques (e.g., [15, 23, 27, 65, 66, 72]).

While Tukey did not explicitly define the goals of EDA, his and others’ writings about EDA [10, 12, 13, 28, 30, 35, 49, 51, 63, 70] mostly focus on the discovery of structure and patterns in the data, and consider EDA a step that precedes formal modeling or confirmatory analysis. However, some [17, 18, 73] argue that EDA also covers profiling [55], or initial data examination to detect data quality issues. Some also state that EDA may occur without formal modeling [29]. As the prior literature lacks a consistent definition of EDA goals, our study helps clarify the nature and scope of EDA by providing evidence that EDA goals include both profiling and discovery. Though the EDA literature emphasizes discovery, we observe that discovery only reliably occurs in open-ended analyses, while all participants engage in profiling across all analyses. We also find that some analysts perform exploration to clean or summarize data without modeling involved. Besides characterizing goals, we also identify common challenges for data exploration and discuss how analysis goals and context affect them.

2.2 Understanding Data Analysis

Many prior studies summarize high-level tasks and challenges in the data analysis process. Some focus on specific user groups and types of analysis. Kwon and Fisher [22] discuss visual analytic
challenges for novices. Conversely, we study experts whose jobs primarily involve data analysis. A few studies [21, 44, 57] examine data analysis and sensemaking within intelligence agencies, which share many challenges with our findings due to exploratory and collaborative nature of their work. However, these agencies often analyze text documents whereas our participants mostly explore structured data. For structured data, Guo [32] describes research programming practices while Fayyad et al. [26] discuss the process of algorithmic data mining.

Another group of works [8, 22, 73] discusses general data analysis process. Closest to our work are the interview studies by Kandel et al. [34] and Alspaugh et al. [8], which derive analysis tasks and challenges based on interview data. However, Kandel et al. mostly focus on analysts that perform direct analyses (i.e., answering predefined questions) and largely overlook tasks and challenges specific to discovery. Meanwhile, Alspaugh et al. interview analysts about exploratory activities akin to this work, but focus only on open-ended exploration and do not discuss how analysis goals affect exploration challenges. In contrast, this study covers exploratory activities across open-ended and directed analyses. We complement these prior studies with the characterization of exploration goals (profiling and discovery) and details of how analysis goals and context affect EDA tasks and challenges. In §3.1 we also discuss how our characterization of the data analysis process differs from those of Kandel et al. and Alspaugh et al.

Some prior studies investigate specific issues in data analysis, e.g., the effects of latency [59] and multiple comparisons [77]. Some study specific tools such as computational notebooks [46, 69], interactive visualizations [11, 76], and dashboards [6]. In contrast, we study day-to-day practices of EDA, which involve many challenges and tools. For exploration challenges, Lam [48] discusses interaction costs for visualizing data such as repetitive physical motions and choosing data subsets. Kidd [47] observes that knowledge workers often focus on implications for decision-making rather than producing generalizable knowledge. Others examine low-level tasks for visual exploration. Amar et al. [9] present a taxonomy of low-level visual analytics tasks. A few studies [20, 38] identify operations that analysts perform to visualize data. Conversely, we focus on the high-level data exploration process.

Prior work also discusses some of the analysis challenges observed in our study. Many studies (e.g., [23, 41, 42, 35, 59]) discuss challenges for data wrangling such as data integration, data cleaning, and handling large data. Here we discuss how data wrangling couples with and impedes exploration.

Many researchers [14, 31, 38, 42, 58] have also noted the importance of analytic provenance. Ragan et al. [58] also characterize types and purposes of provenance in visual analytics. Some studies [37, 42, 44] identify how and why analysts collaborate, and discuss impediments for collaboration. Rule et al. [60] also describe the tension between exploring data and documenting insights for computational notebook users. Batch et al. [11] also comment that visualization tools lack integration with data science workflows.

Though this study shares some findings with prior research, our work is the first, to our knowledge, to overview the day-to-day process and challenges of EDA for both profiling and discovery aspects, including examination of how analysts choose variables to explore and determine when an exploration should stop.

3 Methods
To better understand day-to-day practices of exploratory data analysis, we conducted semi-structured interviews with experienced analysts across both academia and industry.

3.1 Participants
We interviewed 18 analysts (11 male, 7 female) from both academia and industry. As listed in Table 1 the participants worked on various research fields and industrial topics, and held a variety of job titles. In this paper, we use the term “analyst” to generally refer to any participant, as all participants’ jobs primarily involved data analysis.

To recruit participants, we emailed our contacts within our personal and professional networks to forward our recruiting emails to analysts in their organizations. We used a survey to screen participants to those that had at least one year of data analysis experience and performed EDA at least once a month. The participants’ data analysis experience varied from 1-3 years to over 10 years. Most of them performed EDA on a daily or weekly basis, with the least frequent account being biweekly. While our recruitment strategy introduced potential sampling bias in the results, our primary goal is to characterize the space of day-to-day exploratory analysis process and challenges, not to quantify how frequently each specific task occurs. To better quantify these results, other methods, such as surveys, could complement our findings.

3.2 Interview
We conducted semi-structured interviews with one interviewee at a time. Each interview lasted from 45 to 90 minutes. We interviewed analysts at their workplace when possible, and used video calls otherwise. For each interview, we began by describing the study objective, namely to understand current practices and difficulties of exploratory data analysis. We then asked open-ended questions and encouraged interviewees to describe their specific experiences such as “walk us through a recent exploratory data analysis scenario.” Our questions aimed to learn about the following topics:

• What are your analysis goals and outcomes?
• What tasks do you perform during analyses?
• What tools do you use and how do you use them?
• How do you interact with other involved stakeholders?
• How do you choose parts of a dataset to explore?
• How long does an exploration take?
• How do you decide that an exploration is complete?
• What are the key challenges you face in exploratory analysis and how do you handle them?

3.3 Analysis
We analyzed the interview data using an iterative coding method. The first two authors independently coded all data. Throughout the coding process, we discussed disagreements and iteratively revised our codes to ensure consistency across coding sessions. The rest of this paper presents the results from this analysis (summarized in Fig. 1). We also include representative quotes from the interviews to support these results. We use P1-P18 to refer to the participants.

4 Analysis Process and Context
From the interview responses, we first categorize analysis projects based on their overarching objectives and identify two kinds of exploration goals. We then report observed high-level tasks in the analysis process. We also discuss analysts’ context including tools, their operational and domain knowledge, and their collaboration with involved stakeholders.

4.1 Types of Analysis Projects
We asked the interviewees about the objectives of the projects that involved exploratory analysis. We observed four common project types, with varying levels of open-endedness.

Question Answering. All analysts (18/18) reported working on answering business and research questions, so they explored the data to check data quality before answering them. Many analysts (8/18) also noted that their questions, while predetermined, were sometimes open-ended and thus required exploration to discover answers, as P14 said:

"When I start a project, I have a general objective, but I don’t know the specific details. I explore the data to find answers."
A lot of my work is more long-term open-ended research questions such as: how can we characterize the health of the users on our platform?" 

Analysts often produced analysis reports in the form of written documents and presentation slides. They also sometimes built interactive dashboards. 

Open-Ended Exploration. While answering specific questions was more common, several analysts (7/18) noted that they sometimes broadly explored data to summarize and look for new insights without a specific question. P17, a data science consultant, reported that his clients once gave him their website’s data and asked “Please just tell me about my site.” P5, an astronomer, also said: 

“Occasionally we get data that’s surprising like the universe does something we haven’t seen before and a telescope caught it. Then you sit down with the data and think ‘What do I do now?’”

Akin to question answering, analysts often produced reports to describe insights from the open-exploration process.

Model Development. Many analysts (10/18) reported cases where they performed exploratory analysis to prepare for modeling projects such as training machine learning models or developing new metrics and rules. Besides the models, analysts might also deliver reports, or integrate the solutions into dashboards as their project outcomes.

Data Publishing. A few analysts (3/18) explored data while cleaning datasets for publishing on shared repositories, so others could use the datasets for other analyses.

4.2 Exploration Goals

We asked the analysts why they performed data exploration in their analysis projects. From their descriptions, we categorize their goals into two common categories:

Profiling. A common goal for all analysts (18/18) was to learn what the data contained and assess if the data were suitable for the analyses. By broadly looking at the data and their plots, analysts could learn about their shapes and distributions, and detect data quality issues such as missing data, extreme values, or inconsistent data types. They might also check specific assumptions of the data, both in terms of expectations based on domain knowledge and mathematical assumptions required for modeling. By profiling, they learned if the data were ready for the analyses or if they needed to further wrangle the data or acquire more data.
Discovery. Many analysts (13/18) also explored data to discover new insights or hypotheses, as P17 described that his exploration goal was to "be open-minded and learn what the data could tell me." For question answering and modeling projects, analysts might focus on developing intuitions how to answer questions or formulate models such as learning about potential relationships between variables or rankings of feature importance. Some insights also inspired the analysts to broadly explore other relevant factors while some helped them form and investigate specific questions.

Analysts’ focus on exploration goals depended on project objectives. While the EDA literature (reviewed in §2.2) mostly focuses on discovery, we observed that profiling was a more common goal. Projects with fixed questions generally centered on profiling, though surprising observations from profiling sometimes prompted analysts to investigate and discover the causes of the surprises. Meanwhile, open-ended analyses involved both goals. Analysts often first focused on profiling, and shifted their focus to discover new insights when they felt more confident about the data.

4.3 High-Level Tasks in the Analysis Process

From the interviewees’ responses about the tasks they performed in their analyses, we characterize the data analysis process as an iterative process that couples five common high-level tasks: acquisition, wrangling, exploration, modeling, and reporting (as listed and defined in Fig. 2). Some projects might omit some tasks. For example, though exploration often preceded modeling, some analysts (6/18) explored data to clean or summarize data without modeling involved. Some data were also clean and did not require wrangling.

The analysts’ process coupled exploration with many tasks. The analysts regularly explored data to assess if the data were relevant during acquisition. Similarly, they often explored data to decide how to wrangle them. Exploration also helped them discover the need to collect or wrangle more data. In addition, the analysts often reported exploration results to other stakeholders and gathered feedback for more exploration. While we observed less coupling between modeling and exploration, a few analysts examined training data when they observed poor modeling results.

Our characterization of analysis tasks is similar to those of Kandel et al. [42] and Alspaugh et al. [8]. However, as Kandel et al. focus on analysts that typically perform directed analyses (answering predetermined questions), they only list profiling rather than exploration as one of the tasks. Alspaugh et al., whose study focuses on open-ended analyses, augment Kandel et al.’s model by adding exploration as an alternative task to modeling. In contrast, as our study covers exploratory tasks for both directed and open-ended analyses, we found that analysts often explored data prior to modeling. They also often performed similar exploration tasks (examining the data’s values and derived statistics and visualizations, as described in §7.1) to profile data or discover new insights. Thus, we revise Kandel et al.’s model by replacing profiling with a more general exploration task, which subsumes both profiling and discovery goals.

In §4.4 we discuss common challenges in these tasks and report how analysts handled them. Though analysts also explored variations of models and outputs, this paper focuses on data exploration. We consider model diagnostics beyond the scope of this paper.

4.4 Analysis Tools

The interviewees reported using and switching between multiple tools throughout their analyses. A few (P1, P11, P18) were application users who usually looked at and wrangled data in spreadsheets, and visually explored data in Tableau.

The rest (15/18) were programmers who primarily used one language among Python, MATLAB, R, and SAS to analyze data. They usually plotted data with APIs such as Matplotlib [1] and ggplot2 [2]. Several of them also used computational notebooks (e.g., Jupyter [56]) to keep history for repeating and revising their analyses. Some noted that they preferred exploring data via scripting instead of using graphical interfaces as they did not have to switch tools. However, the programmers switched to other tools in some cases. P6 sometimes explored data in Tableau when it could connect to the data sources. Several used spreadsheets to inspect raw data, though they rarely wrangled data in spreadsheets like the application users. Many utilized languages such as SQL and Scalding to fetch and manipulate the data. Some used Tableau [65], Google Data Studio [3], or Microsoft PowerBI [5] for reporting.

Several analysts sometimes had to use domain-specific tools. P3 explored biopsy images from a 3D scan with a specialized tool. A few industrial analysts also noted that their internal data platforms had some support for data wrangling and exploration. As domain-specific tools often had limited features, analysts preferred to use general-purpose tools if possible. However, their data often resided in domain-specific tools and exporting data was sometimes difficult.

4.5 Operational and Domain Knowledge

The analysts typically needed operational and domain knowledge in their analyses. They must know where the data were stored, and how the data were collected and processed. They also needed domain expertise to interpret the data and detect errors. Since analysts usually lacked some required knowledge, they had to learn more about the problem domains and consult other stakeholders.

Job roles also affected the levels of operational and domain knowledge that analysts had. We observed that the analysts had two kinds of job roles relative to their problem domains: domain-specific analysts (9/18) and consultants (7/18), with two (2/18) straddling both roles in different phases of their careers. In academia, most researchers focused on their research topics, but one (P7) was a statistician providing solutions to multiple research domains. In industry, there were both analysts embedded into product teams and consultants who served internal or external clients. As consultants typically worked with a broader set of domains, they often had less domain expertise and relied more on other stakeholders, as P17 said: “Since I’m not embedded with the team, I don’t have the domain context. In this example where I saw elevated counts in the product’s telemetry, I didn’t know what it meant. I could guess, but I’m not on the team, so I have no idea.”

4.6 Stakeholders and Collaboration

We observed that analysts collaborated with a few types of stakeholders over the course of their analysis projects.

Clients. Most analysts (13/18) had clients who prompted them to perform the analyses and were the direct audience for the results. Some analysts were consultants who served external clients while some worked with internal clients within their organizations such as product managers or executives. Analysts often interacted with clients in an iterative fashion. Besides reporting the final results, analysts might share preliminary results and ask the clients for feedback such as verifying if the results matched the clients’ prior knowledge and checking if the analyses aligned with the project goals.
Data owners. Many analysts (10/18) interacted with data engineers or database administrators who curated, processed, or stored the data prior to their analyses. Clients were also sometimes data owners, directly providing the data for the analysts. Analysts often asked the data owners to provide additional information to help them locate, clean, and understand the data since data owners had a better understanding of the format and meaning of the data as well as where the data were stored and how they were processed.

Analysis Team Members. Though the analysts primarily analyzed data on their own, most of them (15/18) were members of analysis teams. Thus, they regularly obtained feedback from fellow analysts and supervisors before presenting to clients. Typical feedback included additional questions to explore, technical advice for analysis techniques and implementation, and suggestions to make the reports easier to understand for the clients. Moreover, a few interviewees noted that they worked jointly with their colleagues on some projects. Two reported splitting the work so each team member could focus on an independent scope and make progress in parallel. Another mentioned that she and her colleague independently analyzed the same data and cross-checked if they arrived at the same results.

Besides supervisors and fellow analysts, a few interviewees had colleagues with more domain expertise in their teams. P3’s medical device research team had a pathologist to give opinions on tumor image analysis. P16, a data science consultant, also reported that his organization included business-oriented “solution managers”, whose duties were to bridge the communication gap between the clients and technical-oriented data scientists and help them define deliverables that matched the clients’ goals.

5 Data Acquisition
We now discuss challenges for data exploration and relevant activities. The first step is to acquire the data necessary for the analysis. All but one interviewee (17/18) reported working with existing datasets. For business analysts, most data were from product logs or customer surveys, while many researchers worked on datasets jointly collected by their research communities. Only some (5/18) had participated in data collection, either by collecting the data themselves or requesting that certain data should be collected.

When working with existing data, finding relevant data were difficult for a few reasons. First, data were often distributed. Several analysts reported that their companies used multiple data storage infrastructures. A few researchers also mentioned that their datasets were collected and published by different research organizations. Thus, analysts typically had to search for data in many places. Moreover, data sources often had insufficient data description, having uninformative column labels and missing or outdated documentation. As a result, analysts had to explore all potential datasets to assess if they were relevant to their analyses.

Some analysts consulted data owners to locate and understand the data. They often received connections to the data owners from their clients or colleagues. However, P14 noted that finding the right people to talk to was difficult since she worked in a remote office.

Analysts also used keyword search to look for relevant datasets in their databases. However, as the same data could be named in many ways, they had to try many different keywords to find the data. For some analysts, their data sources might not have convenient search capability at all. Due to this problem, P2 noted that she was building a searchable database for her organization.

For consulting analysts, they often received their data from the clients. However, the provided data might lack the information necessary to achieve the project goals, requiring the analysts to search for more appropriate data or otherwise terminate the project.

6 Data Wrangling
We observed that analysts often coupled data wrangling with exploration. As analysts received new data, they might want to explore the data. However, data often came from many sources or had an improper format and size for analysis tools. Thus, analysts had to transform the data prior to exploration. Once they explored the data, they might discover that they needed to further handle erroneous values or rescale the data. Due to this coupling, some analysts even associated exploratory analysis with data cleaning.

Akin to prior work [12], several analysts reported that they often spent the majority of their analysis time to wrangle and clean data. As exploration tools often lack support for some wrangling tasks, they had to switch between tools throughout the analysis and migrate data between these tools. We now identify commonly observed wrangling tasks that coupled with or impeded exploration.

6.1 Combining Multiple Datasets
Many analysts (12/18) had to join multiple datasets or integrate similar datasets from multiple sources, both of which presented many challenges. To understand the similarities and differences between datasets, they might have to profile the datasets while combining them. P6 and P10 complained that they often had to join data from over 20 tables. Three analysts also had to use many scripting languages to fetch the data from multiple different platforms.

One common challenge was the inconsistency between data sources. P5, an astronomer, reported that different telescopes published data using various time systems, so she spent a few days just to get the data on the same time systems before she could combine them. P11 also described joining data with different levels of granularity: “Voting data is collected at precinct level while health data is at a state level, and population data is served at zip code level”.

6.2 Dealing with Data Size
Most analysts (15/18) had to deal with data size, which increased data processing time, impeded sharing, or even crashed their analysis tools. P14 mentioned that it took her a few days just to retrieve the data. P3 noted that it was “extremely difficult to share a 250GB file”. Several analysts complained that large datasets did not work in R. P11 was annoyed that his data crashed both Excel and Tableau.

The analysts applied a few strategies to handle large datasets. Some (8/18) reduced data size by sampling the data. P9 and P10 noted that their challenges for sampling included “figuring out how large of a sample size we needed and balancing how long it would take to run” as well as “determining how to get meaningful and representative samples”. Some analysts (8/18) also reduced data size by filtering interesting or relevant subsets based on their domain knowledge or suggestions from domain experts. P15 also applied signal processing techniques to detect signals of interest from audio data, so she could explore just the relevant data. However, analysts might not know in advance how to filter the data until they explored the data.

Some interviewees (4/18) handled large datasets by aggregating them. One difficulty for aggregation was deciding the level of detail. For example, aggregating time series by milliseconds could make the aggregated data too large, while aggregating by year might eliminate important details for the analysis. However, as analysts sometimes lacked specific questions during exploration, they might not initially know the right aggregation level and thus had to re-aggregate the data many times during the exploration.

6.3 Converting Data Formats
Most analysts (15/18) had to convert data into formats expected by their analysis tools. Common formatting tasks included converting file formats and character encodings as well as manipulating data layout such as splitting data columns and reshaping datasets into long formats. A common complaint was that data formatting was time-consuming. Several analysts also complained that they had to manually format spreadsheets that did not have rectangular shapes.
6.4 Deriving New Forms of Data

Many analysts (13/18) derived new forms of data more appropriate for their analyses. Many often rescaled data by normalizing data into certain ranges (e.g., 0 to 1) or applying logarithmic transformation to make them more normally distributed. Several applied low-pass filters or calculated moving averages to reduce noise in the data. P14 and P17 coded new high-level categories from the original low-level categories. As we will discuss in §7.2, analysts also often derived tabular forms of unstructured data (e.g., by calculating statistics) so they could explore and analyze the new data.

6.5 Handling Erroneous Values

Most analysts (13/18) had to handle data errors such as missing data and extreme values. Handling erroneous values was challenging since any decision to filter or impute the data required domain knowledge and might affect downstream analysis. Thus, analysts often explored other aspects of the data and consulted data owners before picking a filter condition or imputation method. Since they might later find that some errors were irrelevant to their analyses, analysts sometimes “piled up” errors and kept exploring until they knew which errors were important to handle.

7 Data Exploration

Once analysts wrangled their data to have a proper format and size, they would explore the data, which sometimes led them to acquire or wrangle more data. In this section, we first summarize observed exploration process with a focus on tabular data, the common data form for all interviewees. We then discuss exploration challenges including choosing variables, handling repetitive tasks, exploring unstructured data, and determining when to stop exploration.

7.1 Observed Exploration Tasks

Analysts usually began exploring by checking what the data contained. For tabular data, analysts would look at table headers and, if available, read the data’s documentation. After knowing what the data were about, they would choose aspects in the data to explore (or stop exploring if the data were irrelevant). As we will discuss in §7.2, the analysts may reduce the number of variables if necessary.

Analysts applied various methods to examine tabular data. To profile the data, more than half of analysts (12/18) directly looked at the data values (e.g., via a print command or spreadsheet software). Many (8/18) computed summary statistics such as the range and central tendencies for continuous variables and value counts for categorical variables. Most analysts (15/18) examined univariate distributions with histograms and count plots. P2 and P7 reported using box plots, while P12 used kernel density plots. Analysts sometimes wrangled a variable during exploration, e.g., by filtering irrelevant and missing values or rescaling the variable.

Analysts examined multivariate distributions for both profiling and discovery goals. They often checked certain distributions to verify their assumptions and investigated why some assumptions did not hold true. If their exploration goal included discovery, they would also explore various combinations of variables to see if they could learn interesting insights. Some of these insights might inspire them to further explore other relevant aspects of the data.

All analysts employed bivariate plots including bar, line, and scatter plots. A few (3/18) used 2D histograms, frequency tables, and contour plots. Many (11/18) also explored plots with more than two variables. In many cases, they encoded the third variable in a plot with colors. P4 and P16 also displayed surfaces of functions with two input variables using 3D plots. However, P16 noted it was sometimes difficult to see relationships from a 3D plot. To examine multiple variables at the same time, several used scatterplot matrices. P2 and P8 also used parallel coordinate plots. If there were too many variables, some analysts grouped variables into small batches to avoid making the scatterplot matrices too large. A few also grouped redundant variables identified via correlation plots.

The analysts reported that a straightforward exploration may take a few hours to a few days. However, the data were often dirty or incomplete, requiring them to acquire or wrangle more data before they continued exploring. Moreover, analysts often had to consult and get feedback from clients or colleagues. However, these stakeholders might not be immediately available to help, so the analysts had to switch to other projects while waiting. For these reasons, exploration may take several days or even weeks.

7.2 How to Choose Variables to Explore?

One common challenge was choosing variables to explore. The interviewees generally reported that they were comfortable exploring datasets with up to one or a few dozen variables. However, many (12/18) had to analyze datasets with several dozens to hundreds of variables and mentioned that the number of variable combinations to explore was a challenge for them. P16 complained that picking variables was “too time-consuming”. P2 said that “choosing variables was harder than plotting itself”. P10 even said he “sometimes skipped plotting if there were too many variables.”

When there were fewer variables, analysts typically examined univariate distributions of all variables and, if possible, all bivariate distributions. If there were too many combinations, they often tried to choose around 10-20 variables using a number of criteria. In addition, they sometimes applied dimensionality reduction techniques.

All interviewees regularly applied domain knowledge to choose variables. For profiling, they often examined variables related to their assumptions based on prior knowledge or suggestions from involved stakeholders. For question answering and modeling, analysts might explore variables they considered relevant to their questions or likely to affect the dependent variables. For open-ended exploration, analysts might wander through data based on what they found interesting. Though a common difficulty was deciding what would be interesting for the audience, several analysts noted that they often explored relationships that might have implications for decision-making. P11 also “drew diagrams between variables with potential relationships” to pick variables.

More than half of the analysts (10/18) reported criteria for dropping variables. They often discarded variables that were parts of their datasets, but irrelevant to their analysis. As datasets often contained duplicate or similar variables, three analysts also used correlation plots to group redundant variables. For each group, they then picked a variable that was the most reliable, having no outstanding data quality issues, and the most understandable for their audience.

Several analysts (7/18) applied statistics and modeling techniques to select variables. Some built simple models, such as shallow decision trees or random forests, to determine important features. P2 and P8 examined variables that correlated with dependent variables. However, these approaches have some limitations. P17 noted that industrial datasets often contained duplicated variables, which might cause some of them to appear less important in the model building approach. P2 also noted that “sometimes there were many things that too were correlated but not important”.

Besides selecting variable subsets, several analysts (6/18) utilized dimensionality reduction techniques to explore large number of variables. Many used principal component analysis (PCA) and plotted the top eigenvectors. P14 also plotted data with t-SNE. However, dimensionality reduction could lead to interpretation difficulty, as P12 noted: “If I have a hyper-dimension that’s combining 1,000 different variables, I can’t explain to my audience what it means.”

7.3 Handling Repetitive Tasks

We found that repetitive tasks also impeded exploration for many analysts (7/18). Some said that they often had to “reinvest the
While all analysts (18/18) regularly worked with structured data, As exploratory analysis is open-ended by nature, a common challenge was difficult to derive a new form of data, the analysts might have to (e.g., text, audio, genomic sequences). P15 also applied signal processing techniques of data and explored the new data instead. P13 and P16 computed structured data (e.g., tables and networks), several (7/18) sometimes analyzed unstructured data (e.g., text). A common challenge was the lack of methods for exploring a large collection of unstructured data. Thus, analysts often derived new forms of data and explored the new data instead. P13 and P16 computed word frequencies for text data. P2 calculated missing call rates for genomic sequences. P15 also applied signal processing techniques to extract signals of interests from audio data. However, when it was difficult to derive a new form of data, the analysts might have to sample the data instead. For example, P3 profiled a large collection of image data by directly examining a small set of samples.

7.4 Exploring Unstructured Data
While all analysts (18/18) regularly worked with structured data (e.g., tables and networks), several (7/18) sometimes analyzed unstructured data (e.g., text). A common challenge was the lack of methods for exploring a large collection of unstructured data. Thus, analysts often derived new forms of data and explored the new data instead. P13 and P16 computed word frequencies for text data. P2 calculated missing call rates for genomic sequences. P15 also applied signal processing techniques to extract signals of interests from audio data. However, when it was difficult to derive a new form of data, the analysts might have to sample the data instead. For example, P3 profiled a large collection of image data by directly examining a small set of samples.

7.5 When Does the Exploration End?
As exploratory analysis is open-ended by nature, a common challenge was deciding when the exploration should end so analysts could move on to the next tasks. When asked how they decided to end an exploration, a handful of interviewees (5/18) responded that they did not always have a definite answer if an exploration was complete. From the interviews, we found that analysts decided to end an exploration based on multiple factors including goal satisfaction, feedback from involved stakeholders, and time constraints.

Goal Satisfaction. All analysts (18/18) often ended an exploration once they satisfied with their goal. For discovery in question answering and modeling projects, they concluded when they had an intuition on how to formulate the answers or the models. For profiling, analysts usually stopped when they had verified all assumptions and felt they had a good sense of the data. Analysts might move on if they thought they had done a sufficient job, as P17 said:

“If I reached a point where I no longer saw glaring issues, I’m done. It does not mean the data is clean. ... However, I’m not seeing any other issues in the data, so they’re small enough that I don’t need to care about them.”

The analysts’ confidence whether they had done a sufficient job varied based on the exploration goals. Analysts generally felt confident about profiling, as P6 noted that “just looking at distributions is not that hard.” However, they were sometimes less confident, especially when the data were large. P3, who profiled samples of large image collections, reported that he felt “confident for 90% of the time”, but sometimes worried that he might have missed important errors in the data. For discovery, analysts generally felt less confident as the goal was more open-ended by nature. P5 even revealed that she never knew if she had comprehensively explored the data when exploring a dataset she had not seen before.

Stakeholder Feedback. Since determining if they had sufficiently achieved the exploration goals could be difficult, analysts generally performed multiple rounds of exploration where they received feedback from team members and clients in between. They then used feedback from team members and clients to assess if they need to further explore the data. Some analysts described that they would stop profiling once their clients and colleagues no longer had concerns about the data. A few also noted that early feedback from colleagues sometimes helped them terminate a low-value project early and let them focus on more important projects.

For open-ended discovery, analysts often ended a round of exploration when they had shareable results. One industrial analyst (P9) mentioned that he usually stopped when he found a result “worth sitting down and discussing.” P5 who used a large public data (P5) for her research mentioned that she stopped exploring when she “discovered enough material to analyze” for a paper. By writing a paper, she then received feedback from the research community, driving her to do further analysis. Analysts also sometimes stopped exploring if the data had nothing interesting.

Time Constraint. Half of the analysts (9/18) cited time limits as a major factor that prompted them to stop exploring. P16 said that “it is okay to explore the data for a few weeks, but after that I will need to start the other parts of the work.” P17 also noted the pressing nature of his work: “we are developing models, and we have to deliver. It’s happened that we have some stones left untiled—sometimes we come back, sometimes we don’t.” For time-sensitive projects, analysts might skip some of the exploration, as P8 said:

“If I have to do it fast, I would not spend most of my time in exploratory analysis. I’ll do some spot checks like just checking the ranges. I would not even look at the distributions and just go right into modeling.”

Since analysts often had limited time to explore large amount of data, it was difficult to perfectly explore all aspects of the data. Thus, they sometimes returned to exploration after moving on to modeling. A few of them also reported that poor modeling results led them to further explore if any data quality issues caused the problems.

8. REPORTING AND SHARING ANALYSIS
As data analysis is iterative and collaborative, analysts had to share their analysis results throughout the process. We now discuss common challenges for sharing analysis results.

8.1 Adjusting Reports to Match Analysis Audience
Many analysts (10/18) needed to adjust their reports to match their analysis goals and the audience’s background. P17 mentioned that his goal was to “produce insights for the audience with the least amount of effort for them to understand.” P18 also noted that “explaining complicated things in a simple way” was the hardest thing in data analysis.

We observed a few strategies for simplifying analysis reports. First, analysts typically avoided using sophisticated plots, such as box plots, in reports for stakeholders with less data analysis expertise. Moreover, while their explorations might have many delicate details, they often presented only the most important findings, such as ones that had implications for decision-making. However, a challenge was that their analysis audience had varying degrees of expectations. Some might even expect to explore the reports themselves, requiring the analysts to create dashboards for the reports.

wheel”, performing similar tasks in each exploration. P8 also wished for a better way to visualize multiple variables at the same time:

“I wish there were a tool that I can just browse through a gallery of each variable’s plot. It would be awesome to just browse through each of the variable’s distribution and outliers, then move on to the next one.”

Despite the abundance of guidelines for data analysis and visualization, some analysts also noted that most tools did not incorporate such knowledge or make them easily accessible. Thus, they had to manually apply the knowledge themselves. One common challenge, especially for programmers, was recalling how to run specific analysis commands. Another common complaint was the lack of good defaults in tools. P13 complained that Matplotlib often required additional customization to make plots look good. P17 was annoyed that many plotting libraries dropped null values by default without indicating that some values were dropped.

To avoid repetitive tasks and ensure that they followed best practices, some programmers compiled templates for commands they often used. P17 even wrote a script to generate a Jupyter notebook that included basic summary plots of all variables in a given dataset and ran basic checks for data quality issues, so he could begin exploration by browsing the notebook without rewriting analysis commands every time. Though templates were useful for saving analysis time, different datasets often had their own subtleties, so analysts needed to adjust their templates based on the data.

We observed a few strategies for simplifying analysis reports. First, analysts typically avoided using sophisticated plots, such as box plots, in reports for stakeholders with less data analysis expertise. Moreover, while their explorations might have many delicate details, they often presented only the most important findings, such as ones that had implications for decision-making. However, a challenge was that their analysis audience had varying degrees of expectations. Some might even expect to explore the reports themselves, requiring the analysts to create dashboards for the reports.
The need to communicate with an audience also led the analysts to align their analyses with the audience’s background. When possible, they would choose concepts that the audience were familiar with. As discussed earlier in §7.2, one criterion to choose a variable from a group of redundant ones was whether the audience would understand it. P8 also reported that he avoided introducing a new metric in his analysis if there was a similar but widely-used metric.

8.2 Analysis Sharing and Provenance
Sharing analysis history across organization was a common challenge for many analysts (8/18), as P14 said: "I often felt that I’m reinventing the wheel, but it’d take me a week to find somebody who already did something similar." A few also reported that their companies tried to use collaboration platforms such as a wiki to share analysis summaries. However, these attempts eventually got abandoned because analysts did not want the extra work to write a summary, in part because they had already presented their analysis via other forms of reports such as slides. P9 also noted the tension between doing more analysis and writing more reports:

“Given a fixed amount of time, do I answer more questions and go as far as I can or do I go slower and write more reports? Finding the balance is a bit hard.”

Analysts also had to revisit their own analysis history to repeat an analysis with new data, or to help them recall prior work when they summarized an analysis for reporting or switched from another project. As discussed earlier in §4.4, some analysts utilized computational notebooks to keep analysis history. However, some analysts had difficulty keeping analysis history, as P12 said:

“I and many other analysts I know often went through an awful lot of charts and later realized there were a few that we wanted but didn’t save along the way.”

9 Design Opportunities
Based on these interview results, we now identify design opportunities for improving data exploration tools.

9.1 Facilitate Rapid Exploration with Automation
From the interviews, we observe many challenges in exploratory data analysis that suggest opportunities to augment data exploration with automation and guidance.

First, as analysts often need to perform repetitive tasks and have limited time to explore data, tools should provide automation to help analysts focus on analyzing data rather than executing routine tasks. While some existing tools provide sensible defaults for plotting commands [72] or help automate chart design [52], these features are not yet available in popular analysis environments such as Python. More importantly, analysts still have to manually create charts one-by-one. As we observe that some analysts apply templates to automate chart generation and wish to browse charts without manually plotting them, tools can recommend charts for analysts to examine [74,75].

As analysts noted in §7.3, tools can incorporate analysis practices into their recommendations. Since analysts should begin exploring data by examining univariate summaries of all variables [53,63], tools can suggest these plots for the analysts [25,75]. When an analyst plots an average of a variable, a tool may augment the plot with variance to convey uncertainty, or suggest robust statistics such as median if there are outliers skewing the average. For large data, a tool may suggest approximate techniques such as sampling, online aggregation [29,34], or density based plots such as histograms and binned scatterplots [16] instead of plotting all individual points.

Another key difficulty for data exploration is choosing variables to explore. We observe that analysts heavily rely on their judgment including determining what variables are interesting and deciding if they have sufficiently explored the data. One potential risk is that analysts may be biased to focus on what they or their stakeholders are interested in, and thus overlook important insights in the data. Tools might reduce this risk by suggesting analysts to explore other aspects of the data and promoting serendipitous discovery.

An important question is how to recommend data for analysts to explore. For profiling, tools may automatically detect and suggest variables with potential issues such as missing values or outliers [43]. For discovery, suggesting data is more challenging as the goal is open-ended. While prior work [64,69,74] leverages statistics for suggestions, we find that analysts mostly pick variables based on their interpretation of semantic relationships between variables, while statistical properties are sometimes irrelevant. Thus, tools should at least allow analysts to steer suggestions based on their interests. An open question is how to design an elicitation method that lets analysts convey domain knowledge such as how the variables could influence each other. Tools might then store and use this information to recommend relevant variables, and possibly help refine hypothesized relationships. As analysts in the same organizations often explore the same datasets at different times, tools may also leverage prior analyses to learn relevancy between variables.

9.2 Support Iterative and Collaborative Workflows
One observation is the lack of support for browsing and searching history [33] in exploration tools. If analysts can efficiently find analyses relevant to certain datasets and variables, they can better understand the data and avoid repeating existing work. Moreover, since an exploration on a dataset can be lengthy, tools should also provide interfaces to annotate important findings so that analysts can later revisit and summarize these findings for their reports. As analysts may not know if they have comprehensively explored the data, surfacing variable coverage [62] may help them identify unexplored directions and perform more comprehensive exploration.

Another key finding is the tight coupling between exploration and other tasks, requiring analysts to switch tools and migrate data. Exploration tools could benefit by either providing support for other tasks such as data wrangling [6] or tightly integrating with existing analysis ecosystems. For example, the JupyterLab data science environment [4] has an extension system that can integrate an exploration tool for Jupyter Notebook users. Moreover, tools should consider using a shared in-memory data format (e.g., [2]) to reduce the need to migrate data due to tool switching. Finally, as analysts often have to create reports or presentations to share with other stakeholders, tools can provide scaffolding to help generate reports from existing analyses and annotations of important findings.

10 Conclusion
This paper presents the results of an interview on exploratory data analysis with 18 analysts across academia and industry. We characterize common exploration goals: profiling (assessing data quality) and discovery (gaining new insights). Though the EDA literature emphasizes discovery, we observe that discovery only reliably occurs in the context of open-ended analyses, whereas all participants engage in profiling across all of their analyses. We also describe how analysis goals and context affect the tasks and challenges in exploratory data analysis. We find that analysts must perform repetitive tasks, yet they may have limited time or lack domain knowledge to explore data. Analysts also often have to consult other stakeholders and oscillate between exploration and other tasks, such as acquiring and wrangling additional data. Based on these observations, we conclude with design opportunities for data exploration tools, such as augmenting exploration with automation and guidance.

Acknowledgments
We thank Interactive Data Lab members and the anonymous referees for their feedback. This work was done when the first author was at the University of Washington. This work was supported by a Moore Foundation Data-Driven Discovery Investigator Award.
visual analysis. *Visualization and Computer Graphics, IEEE Transactions on*, 2014.

[51] L. v. d. Maaten and G. Hinton. Visualizing data using t-sne. *Journal of machine learning research*, 9(Nov):2579–2605, 2008.

[52] J. Mackinlay, P. Hanrahan, and C. Stolte. Show me: Automatic presentation for visual analysis. *IEEE Transactions on Visualization and Computer Graphics (Proc. InfoVis)*, 13(6):1137–1144, 2007.

[53] D. S. Moore and G. P. McCabe. *Introduction to the Practice of Statistics*. WH Freeman/Times Books/Henry Holt & Co, 1989.

[54] S. Morgenthaler. Exploratory data analysis. *Wiley Interdisciplinary Reviews: Computational Statistics*, 1(1):33–44, 2009.

[55] F. Naumann. Data profiling revisited. *ACM SIGMOD Record*, 42(4):40–49, 2014.

[56] F. Perez and B. E. Granger. Project jupyter: Computational narratives as the engine of collaborative data science. *Retrieved September, 11:207*, 2015.

[57] P. Pirolli and S. Card. The sensemaking process and leverage points for analyst technology as identified through cognitive task analysis. In *Proceedings of international conference on intelligence analysis*, vol. 5, pp. 2–4, McLean, VA, USA, 2005.

[58] E. D. Ragan, A. Endert, J. Sanyal, and J. Chen. Characterizing provenance in visualization and data analysis: an organizational framework of provenance types and purposes. *IEEE transactions on visualization and computer graphics*, 22(1):31–40, 2016.

[59] E. Rahm and H. H. Do. Data cleaning: Problems and current approaches. *IEEE Data Eng. Bull.*, 23(4):3–13, 2000.

[60] A. Rule, A. Tabard, and J. D. Hollan. Exploration and explanation in computational notebooks. In *Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems*, p. 32. ACM, 2018.

[61] A. Sarikaya, M. Correll, L. Bartram, M. Tory, and D. Fisher. What do we talk about when we talk about dashboards? *IEEE Transactions on Visualization and Computer Graphics*, 2019.

[62] A. Sarvghad, M. Tory, and N. Mahyar. Visualizing dimension coverage to support exploratory analysis. *IEEE transactions on visualization and computer graphics*, 23(1):21–30, 2017.

[63] H. J. Seltman. Experimental design and analysis. *Online at: http://www.stat.cmu.edu/~hseltman/309/Book/Book.pdf*, 2012.

[64] J. Seo and B. Shneiderman. A rank-by-feature framework for interactive exploration of multidimensional data. *Information Visualization*, 4(2):96–113, 2005.

[65] B. Shneiderman. The eyes have it: A task by data type taxonomy for information visualizations. In *Visual Languages, 1996. Proceedings.*, IEEE Symposium on, pp. 336–343. IEEE, 1996.

[66] C. Stolte, D. Tang, and P. Hanrahan. Polaris: A System for Query, Analysis, and Visualization of Multidimensional Relational Databases. *IEEE Transactions on Visualization and Computer Graphics*, 8(1):52–65, 2002.

[67] J. W. Tukey. *Exploratory data analysis*, vol. 2. Reading, Mass., 1977.

[68] J. W. Tukey. We need both exploratory and confirmatory. *The American Statistician*, 34(1):23–25, 1980.

[69] M. Vartak, S. Rahman, S. Madden, A. Parameswaran, and N. Polyzotis. SeeDB: Efficient data-driven visualization recommendations to support visual analytics. *VLDB 2015*, 8(13):2182–2193, 2015.

[70] P. F. Velleman and D. C. Hoaglin. *Applications, basics, and computing of exploratory data analysis*. Duxbury Press, 1981.

[71] M. Wattenberg, F. Viégas, and I. Johnson. How to use t-sne effectively. *Distill*, 1(10):e2, 2016.

[72] H. Wickham. ggplot2: Elegant Graphics for Data Analysis. Springer, 2009.

[73] H. Wickham and G. Grolemund. *R for data science: import, tidy, transform, visualize, and model data*. “O’Reilly Media, Inc.”, 2016.

[74] G. Wills and L. Wilkinson. Autovis: automatic visualization. *Information Visualization*, 9(1):47–69, 2010.

[75] K. Wongsuphasawat, D. Moritz, A. Anand, J. Mackinlay, B. Howe, and J. Heer. Voyager: Exploratory analysis via faceted browsing of visualization recommendations. *IEEE Trans. Visualization & Comp. Graphics (Proc. InfoVis)*, 2016. *https://idl.cs.washington.edu/papers/voyager*

[76] J. S. Yi, Y. ah Kang, J. T. Stasko, J. A. Jacko, et al. Toward a deeper understanding of the role of interaction in information visualization.