VizRec 2.0: Towards a holistic workflow for visual data exploration [*]

Doris Jung-Lin Lee, Aditya Parameswaran
{jlee782,adityagp}@illinois.edu
University of Illinois, Urbana-Champaign

Abstract

Abstract Placeholder

1 Introduction

With the ever-increasing complexity and size of datasets, there is a growing demand for information visualization tools that help analysts make sense of large amounts of data. Visual data exploration is one of the most commonly used technique that powerfully couples human insights with statistical and data management solutions to help analysts rapidly generate hypothesis, discover interesting trends and patterns, and identify clusters and anomalies. In this paper, we present challenges in the various stages in the cycle of visual analysis, and discuss ongoing and future directions of research that addresses these issues.

Our paper focuses on ongoing research in interactive systems that guides users through the acts of visual data exploration as shown in Figure 1, including searching for a precise visualizations, querying with a vague intent, and recommending visualizations that facilitates better data understanding and awareness. Our presentation of the spiral in Figure 1 does not imply a monotonic sequences of actions, nor are the acts of visual data exploration mutually exclusive from one another, instead the diagram should read as a series of workflow that interleaves and forms an iterative cycle that reinforces one another. For example, as we will discuss in Section 3, better data understanding can lead to better precise visual querying behaviors.

Starting from the innermost spiral, we discuss how precise visual query systems help accelerate the process of finding desired visualizations. Precise visual query system addresses the common problem of having to manually examine large numbers of visualizations in search of a desired pattern, which can be error-prone and inefficient. We discuss our work on *zenvisage* which allows analysts to specify their desired visualization through front-end interactions and automatically returns a ranked list of visualizations that closely matches with the input query.

In Section 2, we highlight examples from our *zenvisage* design study where precise querying alone is insufficient for addressing all the visual querying demands required in real-world use cases. In addition, we find that users often do not have a good idea of what they want to query for without looking at example visualizations or summaries of the data. To improve the flow of visual data exploration, we advocate to make visual query system

Bulletin of the IEEE Computer Society Technical Committee on Data Engineering

[*] Doris: need a better title

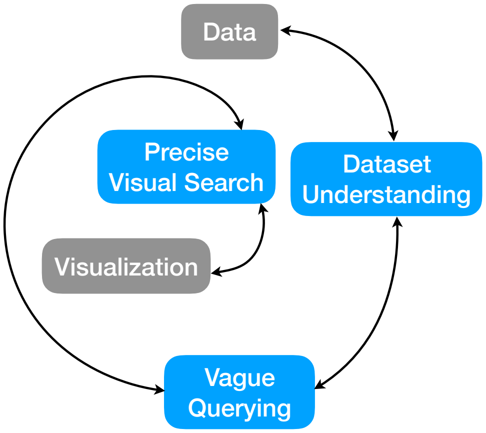


Figure 1: Cycle of visual data exploration.

more expressive by supporting a wider class of vague queries (Section 4) and make it easier to know what to query by recommending visualizations that facilitate data awareness (Section 5).

Section 4 explains why the trade-off between expressiveness and usability in most interactive analytics system is an inherent challenge in making visual query systems more expressive. We discuss a growing class of *intelligent visual querying system* (IVQS) that tries to interpret the 'vagueness' of queries and allow users to tweak or refine their queries through a feedback mechanism.

To address the problem of guiding users to portions of the data that they might be interested in querying, Section 5 introduces systems that help users become more aware of their dataset and visualize where they are in their analysis workflow. The challenge in building these systems involves understanding what types of visualizations should be recommended to facilitate data awareness. As an example, we describe our work on STORYBOARD, a system that provides data summaries and guides users through informative subsets of data. Finally, we discuss related works on how visualizing provenance and situational information can guide users towards more informative analysis actions.

2 Precise Visual Querying

While visual analysis often reveal important anomalies or trends in the data [9, 15], it is often challenging to choose the right piece of data to visualize in order to realize these insights. In this section, we first motivate the use case for visual query systems and describe *zenvisage* as an example of such a system built to address these challenges.

2.1 Motivating Example

Astronomers from the the Dark Energy Survey (DES) are interested in finding anomalous time series to discover astrophysical transients (objects whose brightness changes dramatically as a function of time), such as supernova explosions or quasars [5]. When trying to find celestial objects corresponding to supernovae, which have a specific pattern of brightness over time, scientists need to individually inspect the visualizations of each object until they find ones that match the pattern. With more than 400 million objects in their catalog, each having their own set of time series brightness measurement, the process of manually exploring a large number of visualizations is not only error-prone, but also overwhelming for scientists who do not have extensive knowledge about their dataset.

The astronomy use case highlights a common challenge in exploratory data analysis (EDA). There is often a large space of possible visualizations that could be generated from a given dataset and manual search through this large collection is inefficient. Popular visualization authoring tools such as Tableau and Excel focus on presenting one visualization at a time and there is no systematic way to create, compare, and query large collections of visualizations.

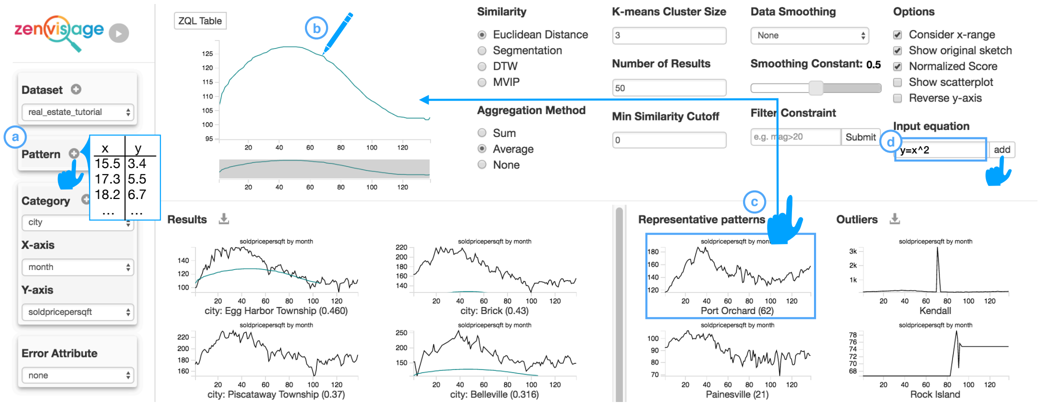
2.2 Effortless Data Exploration with *zenvisage*

The challenges discussed in the previous section point to the need for a tool that enables users to create and search through large collections of visualizations. To this end, we developed *zenvisage*, a *precise visual querying system (PVQS)* that accepts precise queries in the form of a desired pattern specified through frontend interactions and returns a ranked list of visualizations that look similar to the input pattern [24]. *zenvisage* is built on top of a querying language called ZQL, which provides a mechanism for managing collections of visualizations. Contrary prior work on visualization languages for specifying visual encodings of individual visualizations [25, 27], ZQL supports high-level queries over visualization collections, such as composing, sorting, filtering a collection of visualization. ZQL functionals and primitives can be constructed into rich and expressive query semantics, with functionalties including:

- Finding top-k visualizations whose y values are most or least similar from a queried visualization. (e.g. Find cities with sold price over time similar to Manhattan. Varying along CITY while keeping X = TIME,Y = AVG(PRICE) fixed.)
- Comparing across a collection of visualizations by iterating over one or more x, y, z attributes while fixing other attributes. (e.g. Find an y attribute that varies with time similarly how average price changes over time)
- Finding a pair of X and Y axes where two specific visualization instances differ the most. (e.g. Finding pairs of attributes where visualizations for the products 'stapler' and 'chair' differ the most.)

Given a ZQL query, *zenvisage* parses the query into a graph of visual component nodes (containing visualization information, such as X, Y columns) and task nodes (common and user-defined primitives for processing visual components, such as sort or filter). *zenvisage* then performs query optimization to merge together multiple nodes, as well as reducing the processing time required for individual visualization components. Using the optimized query plan, the executor compiles visual nodes into SQL queries for retrieving the visualization data and postprocesses the result via the defined operations.

While ZQL provides powerful mechanism for expressively specifying queries on large collections visualizations, writing ZQL queries can be daunting for novice users. Therefore, we extracted a typical workflow of visualization querying (finding top-k most similar visualization from a collection with fixed X,Y while varying Z) to allow users to formulate ZQL queries through interactions. The user can either perform frontend interactions mapped onto ZQL queries or directly input ZQL queries through a table input. The query results are rendered as a ranked list of visualizations in the results panel in the interface. *zenvisage* is a full-fledged visual querying system that supports a variety of querying interactions as illustrated in Figure 2. In the following section, we will discuss the design process of the interactions in this precise visual query system and the lessons that we have learned for designing future visual data exploration systems.



Dataset
real_estate_tutorial

Pattern

x	y
15.5	3.4
17.3	5.5
18.2	6.7
...	...

Category
city

X-axis
month

Y-axis
soldpricepersqft

Error Attribute
none

Similarity
- ● Euclidean Distance
- ○ Segmentation
- ○ DTW
- ○ MVIP

Aggregation Method
- ○ Sum
- ● Average
- ○ None

K-means Cluster Size: 3

Number of Results: 50

Min Similarity Cutoff: 0

Data Smoothing: None

Smoothing Constant: 0.5

Filter Constraint: e.g. mag>20 Submit

Options
- ☑ Consider x-range
- ☑ Show original sketch
- ☑ Normalized Score
- □ Show scatterplot
- □ Reverse y-axis

Input equation: y=x^2 add

Figure 2: *zenvisage* offers a variety of querying modalities, including: a) uploading a sample pattern from an external dataset as a query, b) sketching a query pattern, c) dragging-and-dropping an existing pattern from the dataset, and d) inputting an equation as a query.

3 Hypothesis Formation and the cycle of visual analysis

3.1 Visual Querying in the *Sensemaking Framework*

In developing *zenvisage*, we collaborated with scientists from astronomy, genetics, and material science in a year-long participatory design process [13]. In particular, we study how various features impact an analyst's ability to rapidly generate new hypothesis and insights and perform visual querying and analysis. Our findings not only offers design guidelines for improving the usability and adoption of next-generation PVQSs, but more importantly, can be applied to the context of supporting the full cycle of visual data exploration.

3.2 The Need for Complex, Vague, and Expressive Querying

When users query with a PVQS, they often need to translate their ambiguous, high-level questions into an plan that consists of multiple interactions to incrementally address their desired query. Participants in our *zenvisage* design study often created unexpected workflows that chained together analysis steps consisting of multiple interactions and controls. For example, geneticists in our study repeatedly explored representative trends to gain an overall sense of the typical profiles that exist in their dataset and queried mainly through drag-and-drop of these representative trends. Variations to their main workflow also include changing cluster sizes and display control settings to offer them different perspectives on the dataset.

The expressiveness of PVQSs comes from the multiplicative effect of stringing together combinations of interaction sequences into a customized workflow. Designing features that diversifies potential variations and helps the creation of multiple analysis workflows expands the space of actions that could be performed during the analysis. However, even with many supported interactions, there were still complex multi-step queries that could not be expressed through this framework. In Section 4, we highlight the challenges of PVQSs in supporting these types of queries, the need for tools that support complex and vague querying, and several promising directions of ongoing research in this area.

3.3 Top-down and Bottom-up Querying Modalities

We employed Pirolli and Card's [19] information foraging theory to contextualize our study results. Pirolli and Card's notional model distinguishes between information processing tasks that are *top-down* (from theory to data) and *bottom-up* (from data to theory). In the context of visual querying, users employ top-down approaches by starting with a hypothesis on what patterns to look for and express it through sketching or inputting an equation (Figure 2b,d). On the other hand, bottom-up approaches originate from the data (or equivalently, the visualization). For example, the user may drag and drop a visualization of interest in the dataset as the input query or upload a visualization from an external dataset (Figure 2a,c). These two modalities of querying are reminiscent of the browsing and searching behaviors on the Web, which derives from the successful application of foraging theory to Web Search [17].

While the usage of each querying feature may vary from one participant to the next, our interactions with the scientists showed that *bottom-up querying via drag-and-drop was more intuitive and more commonly used than top-down querying methods when the users have no desired patterns in mind*, which is commonly the case for exploratory data analysis. One of the main reason why participants did not find sketching useful was that they often do not start their analysis with a pattern in mind. Later, their intuition about what to query is derived from other visualizations that they see in the PVQS, in which case it made more sense to query using those visualizations as examples directly. Similarly, while functional fitting is a common operation in scientific data analysis, querying by equation is also unpopular, since it is challenging to formulate functional forms in an prescriptive, ad-hoc manner without seeing what the common patterns in the dataset are.

A key design principle that came from this study was the need for visualization recommendations that can help analysts jump-start their exploration. For example, we found that many users made use of the recommended representative trends and outliers visualizations provided by *zenvisage* as contextual information to better understand their data or to query based on these recommended visualizations.

As evident from the representative and outliers in *zenvisage*, recommendations facilitate smoother flow of analysis by closing the loop between the two modalities of querying and exploration, thus ensuring that user is never stuck or out of ideas at any point during the analysis. Typically, visualization recommendation systems seeks to accelerate the process of discovering interesting aspects of the data by broadening exploration. In Section 5, we advocate recommendation systems should not only focus on data discoverability aspect of exploration, but also contribute towards helping users become more aware of the distributions in their data and the context of their analysis.

4 Vague and Complex Querying

Doris: need a better title describing this, make sure the Figure reflects these title changes

4.1 Challenge: Usability-Expressivity Tradeoff

The need for vague and complex querying stems from the inevitable design trade-off between query expressivity and interface usability in interactive data exploration systems [15, 11]. For example, the *zenvisage* interface was unable to support high-level queries that involved the use of vague descriptors for matching to specific data characteristics, such as finding light curves that are flat and 'without noise', or patterns that 'exhibits irregularities'. While this could be expressed through user-defined functions in the underlying querying language ZQL, the learning curve and engineering cost is high.

This tradeoff is observed not only in visual data exploration systems, but also true for general ad-hoc data querying. For example, while querying language such as SQL are highly expressive, formulating SQL queries that maps user's high-level intentions to specific query statements is challenging[11, 12]. Therefore, query construction interfaces have been developed to address this issue to enable direct manipulation of queries through graphical representations [1], gestural interaction [16], and tabular inputs [32, 6]. Form-based query builders often consist of highly-usable interfaces that ask users for a specific set of information mapped onto a pre-defined query. However, form-based query builders are often based on query templates with limited expressiveness in their semantic and conceptual coverage, which makes it difficult for expert users to express complex queries.

The extensibility of these systems or querying language also comes with the high engineering cost, as well as potentially overloading the users with too many potential options to chose from. There is a need for tools that is enables users to formulate rich and complex queries, yet highly usable even for novices.

4.2 Ongoing research and opportunities

Given the tradeoff between expressivity and usability, we can not assume a one-size-fit-all PVQS that could fit the need for users of different expertise levels and workload. In this section, we discuss a growing class of *intelligent visual querying system* (IVQS) that works around this problem by taking into account queries of varying degrees of specificity. We describe three different challenges in vague querying. While our analysis is not limited to natural language interfaces, we use this classification scheme to provide an analogy for types of vague queries that an analyst might specify during visual data exploration.

Lexical Ambiguity: Lexical ambiguity involves the use of vague descriptors in the input queries. Our previous example of queries that could not be expressed in the *zenvisage* interface showcases one example of lexical ambiguity, where the PVQS can not map the vague term 'irregular' or 'noisy' into the appropriate series of analysis steps required to find these patterns. Doris: Not sure if its worthwhile to include a couple sentences about Tarique's regex/NLP work here. e.g. the 'up and then down' example. Resolving these lexical ambiguities has been a subject of research in natural language interfaces (NLIs) for visualization specification, such as DataTone [8] and Eviza [23]. These NLIs detects ambiguous quantifiers in the input query (e.g. "Find large earthquakes near California"), and then displays ambiguity widgets in the form of a widget to allow the user to specify what is the definition of 'large' in terms of magnitude and how many miles radius do we consider 'near'. These ambiguity widgets not only serve as a way to provide feedback to the system for lexically vague queries, but also is a way for displaying interpretable explanations of how the system is interpreting the input queries. An IVQSs can be thought of as a layer on top of PVQS (for functionalities such as shape-matching, filtering), which choses appropriate *parameters* to the PVQS to achieve the user's desired querying effects.

Syntactic Ambiguity: Syntactic ambiguity is related to the vagueness in the specification of how the query should be structured or ordered. For example, DataPlay introduced the idea of syntax non-locality in SQL, in which switching from an existential (at least one) to a universal (for all) quantifier requires major structural changes to the underlying SQL query. They have built a visual interface that allowed users to directly manipulate the structure of the query tree in tweaking the query to its desired specification. IVQSs that resolve syntactic ambiguities either map the vague queries into to *a series of multi-step workflows* to be executed in the PVQS or allow users to tweak the query representation directly. The query specification and tweaking is done in a declarative manner in that the mechanism in which the visualized workflow gets translated to the underlying language is hidden from the end-user.

Semantic Ambiguity: Semantic ambiguity arises when the user does not specify their intent completely or explicitly, which is often the case in the earlier stages of the visual data exploration. NLIs for visual data exploration such as Evizeon [10] makes use of anaphoric references to fill in incomplete follow-on queries. For example, when a user says 'Show me average price by neighborhood', then 'by home type', the system interprets the latter partial specification as continuing the context of the original utterance related to average price on the y-axis. Semantic ambiguity can also be thought of as being composed of one or more lexical and syntactical ambiguity. For example, in Iris [7], a user can specify a vague, high-level query such as 'Create a classifier', then Iris makes use of nested conversations to inquire about what type of classifier to chose and what features to use in the model to fill in the details of the structure and parameters required, thus resolving the syntactic and semantic ambiguity. A semantically vague query may or may not be expressible through a single PVQS, since the operations involved in the query may not be covered by the limited workflow combinations in the PVQS. Doris: Might be good to include three screenshot side-by-side of each of these types of vagueness in querying, situation in which people do vague querying, and systems that tries to address it. Are we allowed to take screenshots from other people's papers or do we need to ask them for permission?

5 Towards Dataset Understanding

One of the key goals of visual data exploration is to promote a better understanding of the dataset to enable users to make actionable decisions. While our focus in the previous sections have focused on intention-driven queries, where users have some knowledge of what types of questions he may be interested in. This section discusses systems that helps users become more aware of their dataset and visualize where they are in their analysis workflow.

Situations where there is an absence of explicit signals from the user can happen when a user is at the beginning of their analysis (commonly known as the 'cold-start' problem) or when the user doesn't know what to query for, which is the finding derived from our *zenvisage* study, described in Section 3. In this section, we will describe STORYBOARD, a system that provides data summaries and guides users through informative subsets of data, as an example of a system that promotes distribution awareness in a query-free scenario. Then, we will discuss other types of data understanding during dynamic visual data exploration to highlight the challenges and opportunities ahead in this space.

5.1 STORYBOARD: Promoting Distribution Awareness of Data Subsets with Summary of Visualizations

Common analytics tasks, such as causal inference, feature selection, and outlier detection requires studying the distributions or patterns at different levels of data granularity [2, 30, 9]. However, it is often hard to know *what* subset of data contains an insightful distribution to examine. In order to explore different data subsets, a user would first have to construct a large number of visualizations corresponding to all possible data subsets, and then navigate through this large space of visualizations to draw meaningful insights. While there are some related work in database literature in constructing informative summaries that help guide users through the complex schema of object-oriented databases[31, 14], these are often focused on attribute level information, rather than information about derived from the actual data values. The lack of a systematic way to perform these exercises makes the process of manually exploring distributions from all possible data subsets tedious and inefficient [20, 21].

To this end, we present STORYBOARD, an interactive visualization summarization system that automatically selects a set of visualizations to summarize the distributions within a dataset in an informative manner. Figure **??** illustrates an example dashboard generated by STORYBOARD from the Police Stop Dataset [18], which contains records of police stops that resulted in a warning, ticket, or an arrest. The attributes in the dataset include driver gender, age, race, and the stop time of day, whether a search was conducted, and whether contraband was found. We requested STORYBOARD to generate a dashboard of 9 bar chart visualizations with x-axis as the stop outcome (whether the police stop resulted in a ticket, warning, or arrest/summons) and y-axis as the percentage of police stops that led to this outcome. First, at the top of our dashboard, STORYBOARD highlights three key data subsets that results in a high arrest rate, which looks very different trend than the overall (where the majority of stops results in tickets). Following along the leftmost branch, we learn that even though in general when a search is conducted, the arrest rate is almost as high as ticketing rate, when we look at the Asian population, whether a search is conducted had less influence on the arrest rate and the trend resembles more like the overall distribution.

While such summary dashboards are useful for making sense of relationships between data subsets, finding effective visualizations to summarize a dataset is not as trivial as picking individual visualizations that maximizes some statistical measure, such as deviation [26], coverage [22], or significance testing [2], which can often result in misleading summarizations. The key idea behind our work is how users formulate their expectations regarding an unseen visualization in a *data subset lattice*. We make use of the idea of a data subset lattice from data cube literature to organize the relationships between different visualization. A visualization is a *parent* of another visualization if the latter visualization can be derived from the first visualization by adding one additional filter

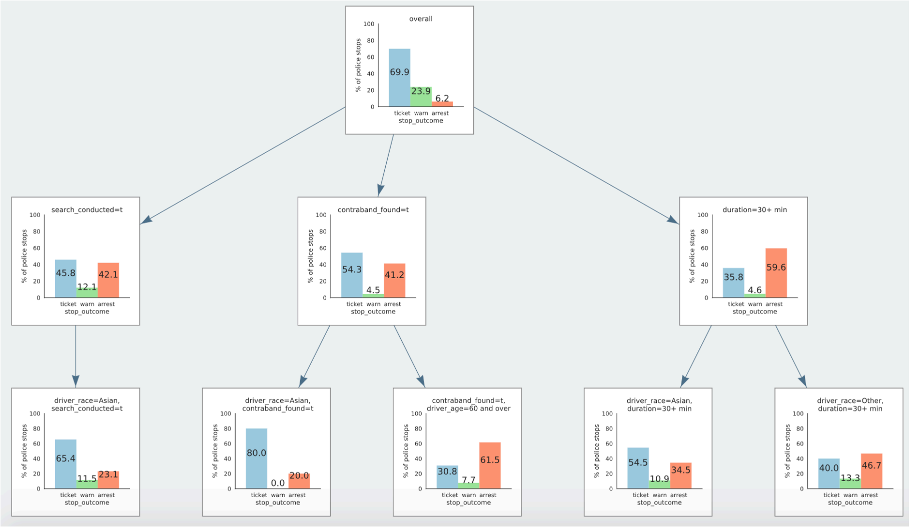


Figure 3: Example dashboard generated by STORYBOARD summarizing the key insights in the Police dataset.

constraint.

Our formative user study showed that people naturally form their expectations based on one or more observed parents and that seeing a parent that well describes the unseen visualization leads participants to better estimate the unseen visualization. More importantly, in the absence of an informative parent or in the presence of multiple parents, participants can be misled to form an inaccurate expectation that exhibit higher variance.

Given these insights, the goal of our system is to select *interestingness* and *informativeness* visualizations that can help them make more accurate predictions regarding the unseen visualizations. To model the informativeness of an observed parent in the context of an unseen visualization, we characterize the capability of the parent in predicting the unseen visualization. Our study shows that a visualization is *informative* if its data distribution closely follows the data distribution of the unseen child visualization, since the visualization helps the analyst form an accurate mental picture of what to expect from the unseen visualization. While informative parents contribute to the prediction of an unseen visualization, the most interesting visualizations to recommend are those for which *even the informative parents fail to accurately predict or explain the visualization*. Detailed treatments of our metrics and algorithms can be found in our technical report. Doris: (CITE PLACEHOLDER) Can we put a version of the STORYBOARD paper on arxiv so that we can cite it?

The effectiveness of STORYBOARD largely comes from how it helps analysts become more distributionally aware of the dataset. We define *distribution awareness* as the aspect of data understanding in which analysts make sense of the key distributions across different data subsets and their relationship in the context of the dataset. So that even though it may be infeasible to examine all possible data subsets, with distribution awareness, the analyst will still be able to draw meaningful insights and establish correlations about related visualizations by generalizing their understanding to make predictions regarding the unseen visualizations. Our user study evaluations show that facilitating distribution awareness through STORYBOARD guides users to make better predictions regarding unseen visualizations, ranking attribute importance, and retrieval of interesting visualizations compared to the baselines.

5.2 From Distributional to Contextual Awareness: Challenges and Opportunities

The notion of distribution awareness is useful when we are looking at user understanding at one static point in time of the analysis (e.g. during cold start). In this section, we introduce a complementary notion of data understanding called *contextual awareness*, which is essential when considering the dynamic setting of visual data exploration in the context of an analytic workflow.

Contextual awareness is the aspect of data understanding related to understanding the *situation* (what is the information that I'm currently looking and how did it come about?) and *provenance* (what have I explored in the past and where should I look next?) of the data. Situational understanding involves recognizing what data is in the current scope of analysis, including making sense of the data attributes and schema and keeping track of what filter or transformations have been applied to the displayed data. Provenance understanding is related to the user's past analysis actions on the data. As an example, an analyst may be interested in how sales price of a product changes as a function of other dimensions variables, such as geographic location, year sold, and product type. Situation information informs him that he is looking at a bar chart with X=TYPE, Y=AVG(PRICE), whereas provenance information points to the fact that he should explore the geographic dimension, since he has already explored the temporal attribute YEAR.

Mechanisms that facilitate distribution awareness for users can effectively couple with contextual awareness in dynamic exploration situations to help update the user's mental model on the current data context. For example, the representative and outlier patterns in *zenvisage* provides summaries of data in context. When a dataset is filtered, the representative trends are updated accordingly. By being aware of both the context and the distributions, the users becomes distributionally aware of how the typical patterns and trends of the distributions changes in a particular context.

Within a dataset, provenance is essential to help users navigate and provide users with sense of coverage and completion. While the problem of data provenance has been well studied in database literature [3, 4, 29], the effects of showing provenance information to users during data analysis is an important but underexplored area. The notion of adding navigational cues to guide exploration in visual information spaces was first proposed by Willet et al.[28] in work on *scented widgets*. Scented widgets are inspired by Pirolli and Card's theory of 'scent' in foraging. The widgets adds to existing interfaces by embedding visualizations that provide informational 'scents', such as histogram distributions of how popular a particular value is among users or using color to encode the size of a dataset in a drop-down menu. Recently, Sarvghad et al. [22] have extended the idea of scented widgets to incorporate dimension coverage information during data exploration, including which dimensions have been explored so far, in what frequency, and in which combinations. Their study show that visualizing dimension coverage leads to increased number of questions formulated, findings, and broader exploration than participants who had no access to coverage information. Interpretable and non-disruptive cues that enables users to visualization provenance history helps sustain contextual awareness and guides users towards more informative next steps in their analysis.

Note that while the discussion above have been focused on how to design systems that can help facilitate these aspects of user's awareness in dataset understanding, these ideas can be generalized to principles in designing the types of intelligent querying systems discussed in Section 4. An intelligent visual exploration system needs to be distributionally, contextually and situationally aware, by make use of information about the data (distribution awareness), the analytic context, and situation jointly in making timely recommendations. For example, contextual awareness can inform the system that the user's current situation (x,y, encoding, etc.), while a distributionally aware system may recommend a highly-skewed data subset as interesting, a situational aware system may realize a variable have been explored extensively in the past and recommends it accordingly. In other words, these intelligent visual query system not only needs to facilitate these aspects of data understanding, but also need to make use of this information to make inference and recommendations in an interpretable manner that can guide analysts towards meaningful stories and insights for further investigation.

6 Concluding Remarks

In this paper, we advocate supporting a desiderata consisting of 3'I's in the cycle of visual data exploration:

- **Informative**: Section 2 discusses how precise visual query systems provide informative visualizations to accelerate the process of data discovery.

- **Interactive and iterative**: Section 4 Joining the flow, query refinement, dialogue (not a one-shot query), feedback and recommendation, expressivity (how easy is it to express what to do via interactions) and diversity of actions that could be performed.
- **Integrated**: Section 5 discusses the challenges and opportunities in moving from intention-driven querying to facilitating more integrated data understanding and awareness during the analysis workflow.

References

[1] Azza Abouzied, J Hellerstein, and A Silberschatz. Dataplay: interactive tweaking and example-driven correction of graphical database queries. *Proceedings of the 25th annual ACM symposium on User interface software and technology*, pages 207–217, 2012.

[2] Anushka Anand and Justin Talbot. Automatic Selection of Partitioning Variables for Small Multiple Displays. 2626(c), 2015.

[3] Peter Buneman, Adriane Chapman, and James Cheney. Provenance management in curated databases. In *Proceedings of the 2006 ACM SIGMOD International Conference on Management of Data*, SIGMOD '06, pages 539–550, New York, NY, USA, 2006. ACM.

[4] Y. Cui and J. Widom. Lineage tracing for general data warehouse transformations. *The VLDB Journal*, 12(1):41–58, May 2003.

[5] Drlica Wagner et al. Dark Energy Survey Year 1 Results: Photometric Data Set for Cosmology. 2017.

[6] David W. Embley. Nfql: The natural forms query language. *ACM Trans. Database Syst.*, 14(2):168–211, June 1989.

[7] Ethan Fast, Binbin Chen, Julia Mendelsohn, Jonathan Bassen, and Michael Bernstein. Iris: A Conversational Agent for Complex Tasks. *CHI 2018*, 2018.

[8] T.a Gao, M.b Dontcheva, E.a Adar, Z.b Liu, and K.c Karahalios. Datatone: Managing ambiguity in natural language interfaces for data visualization. *Proceedings of the 28th Annual ACM Symposium on User Interface Software & Technology - UIST '15*, pages 489–500, 2015.

[9] Jeffrey Heer and Ben Shneiderman. Interactive Dynamics for Visual Analysis. *ACM Queue*, 10(2):30, 2012.

[10] Enamul Hoque, Vidya Setlur, Melanie Tory, and Isaac Dykeman. Applying Pragmatics Principles for Interaction with Visual Analytics. *IEEE Transactions on Visualization and Computer Graphics*, (c), 2017.

[11] H. V. Jagadish, Adriane Chapman, Aaron Elkiss, Magesh Jayapandian, Yunyao Li, Arnab Nandi, and Cong Yu. Making database systems usable. In *Proceedings of the 2007 ACM SIGMOD International Conference on Management of Data*, SIGMOD '07, pages 13–24, New York, NY, USA, 2007. ACM.

[12] Nodira Khoussainova, YongChul Kwon, Magdalena Balazinska, and Dan Suciu. Snipsuggest: Context-aware autocompletion for sql. *Proceedings of the VLDB Endowment*, 4(1):22–33, 2010.

[13] Doris Jung-Lin Lee, John Lee, Tarique Siddiqui, Jaewoo Kim, Karrie Karahalios, and Aditya G. Parameswaran. Accelerating scientific data exploration via visual query systems. *CoRR*, abs/1710.00763, 2017.

[14] J McHugh, S Abiteboul, R Goldman, D Quass, and J Widom. Lore: A database management system for semistructured data. *SIGMOD Record*, 26(3):238–247, 1997.

[15] Kristi Morton, Magdalena Balazinska, Dan Grossman, and Jock Mackinlay. Support the Data Enthusiast: Challenges for Next-Generation Data-Analysis Systems. *Proceedings of the VLDB Endowment, Volume 7, pp. 453–456, 2014*, 7:453–456, 2014.

[16] Arnab Nandi, Lilong Jiang, and Michael Mandel. Gestural query specification. *Proceedings of the VLDB Endowment*, 7(4):289–300, 2013.

[17] Christopher Olston and E D H Chi. ScentTrails: Integrating browsing and searching on the Web. *ACM Transactions on ComputerHuman Interaction TOCHI*, 10(3):177–197, 2003.

[18] E. Pierson, C. Simoiu, J. Overgoor, S. Corbett-Davies, V. Ramachandran, C. Phillips, and S. Goel. A large-scale analysis of racial disparities in police stops across the united states, 2017.

[19] Peter Pirolli and Stuart Card. The Sensemaking Process and Leverage Points for Analyst Technology as Identified Through Cognitive Task Analysis. A Notional Model of Analyst Sensemaking.

[20] S Sarawagi, R Agrawal, N Megiddo, Generalitat Valenciana Ajuntament Valencia Univ Politecn Valencia, and E T H Zurich Oracle Sybase Softlab Iberia Edbt Fdn. Discovery-driven exploration of OLAP data cubes. *6th International Conference on Extending Database Technology (EDBT 98)*, pages 168–182, 1998.

[21] S. Sarawagi. User-adaptive exploration of multidimensional data. *Proc of the 26th Intl Conference on Very Large*, pages 307–316, 2000.

[22] Ali Sarvghad, Melanie Tory, and Narges Mahyar. Visualizing Dimension Coverage to Support Exploratory Analysis. *IEEE Transactions on Visualization and Computer Graphics*, 23(1):21–30, 2017.

[23] Vidya Setlur, Sarah E Battersby, Melanie Tory, Rich Gossweiler, and Angel X Chang. Eviza: A Natural Language Interface for Visual Analysis. *Proceedings of the 29th Annual Symposium on User Interface Software and Technology - UIST '16*, pages 365–377, 2016.

[24] Tarique Siddiqui, Albert Kim, John Lee, Karrie Karahalios, and Aditya Parameswaran. Effortless data exploration with zenvisage: An expressive and interactive visual analytics system. *Proc. VLDB Endow.*, 10(4):457–468, November 2016.

[25] 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):1–14, 2002.

[26] Manasi Vartak, Samuel Madden, and Aditya N Parmeswaran. SEEDB : Supporting Visual Analytics with Data-Driven Recommendations. 2015.

[27] Leland Wilkinson. *The Grammar of Graphics (Statistics and Computing)*. Springer-Verlag, Berlin, Heidelberg, 2005.

[28] Wesley Willett, Jeffrey Heer, and Maneesh Agrawala. Scented widgets: Improving navigation cues with embedded visualizations. *IEEE Transactions on Visualization and Computer Graphics*, 13(6):1129–1136, 2007.

[29] Allison Woodruff and Michael Stonebraker. Supporting fine-grained data lineage in a database visualization environment. In *Proceedings of the Thirteenth International Conference on Data Engineering*, ICDE '97, pages 91–102, Washington, DC, USA, 1997. IEEE Computer Society.

[30] Eugene Wu and Samuel Madden. Scorpion: Explaining Away Outliers in Aggregate Queries. *Proceedings of the VLDB Endowment*, 6(8):553–564, 2013.

[31] Cong Yu and H. V. Jagadish. Schema summarization. In *Proceedings of the 32Nd International Conference on Very Large Data Bases*, VLDB '06, pages 319–330. VLDB Endowment, 2006.

[32] Moshe M Zloof. Query by Example. *National Computer Conference*, pages 431–438, 1975.