

# How are visual query systems used in practice: A Design Study with Zenvisage

## ABSTRACT

The increasing availability of rich and complex data in a variety of scientific domains poses a pressing need for tools to enable scientists to rapidly make sense of and gather insights from data. One proposed solution is to design visual query systems (VQSs) that allow scientists to interactively search for desired patterns in their datasets. While many existing VQSs promise to accelerate exploratory data analysis by facilitating this search, they are not widely used in practice. Through a year-long collaboration with scientists in three distinct domains—astronomy, genetics, and material science—we study the impact of various features within VQSs that can aid rapid visual data analysis, and how VQSs fit into scientists’ analysis workflow. Our findings offer design guidelines for improving the usability and adoption of next-generation VQSs, paving the way for VQSs to be applied to a variety of scientific domains.

## KEYWORDS

Visual analytics, visualization, exploratory data analysis, visual query, scientific data.

## 1 INTRODUCTION

Two-dimensional line charts are one of the most ubiquitous visualization types, not only for time series but also for understanding the relationships between multiple measures variables.

From high-throughput genome sequencing, to multi-resolution astronomical imaging telescopes, to at-scale physical testing of battery candidates, many fields of science and engineering are facing an increasing availability of large volumes of complex data [4, 8], holding the key to some of the most pressing unanswered scientific questions of our time, such as: How does a treatment affect the expression of a gene in a breast cancer cell-line? Which battery components have sustainable levels of energy-efficiency and are safe and cheap to manufacture in production? While data analysis is central to a scientist’s knowledge discovery process, scientists often lack the extensive experience to deal with data of this scale and complexity in a way that can facilitate rapid insight discovery [17].

To explore their data, many scientists currently create visualizations, either programmatically using tools (such as `ggplot` or `matplotlib`), or visualization construction interfaces (such as Excel or Tableau) [23, 30]. In either case,

scientists are required to specify exactly what they want to visualize. For example, 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 (often numbering in the thousands) until they find ones that match the pattern. Similarly, when trying to infer relationships between two physical properties for different subsets of battery electrolytes, scientists need to individually visualize these properties for each subset (out of an unbounded number of such subsets) until they identify relationships that make sense to them. This 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.

One potential solution for this challenge of manually exploring a large collection of visualizations are systems that allow users to specify desired visual patterns, via a high-level specification language or interface, with the system automatically traversing all potential visualization candidates to find and return those that match the specification. We define such systems to be *Visual Query Systems*, or VQSs for short. There are a number of VQSs that have been introduced in the literature [14, 22, 31, 34, 35]. For example, Google Correlate [22] and QuerySketch [35] allow users to draw a trend of interest, with the system automating the search to find matching visualizations.

Not surprisingly, when asked about the potential viability of VQSs in aiding scientific data analysis, many scientists indicated that VQSs could be useful in mitigating the challenge of visualization exploration described earlier—since it automates the painful manual exploration of visualizations to find desired patterns. Yet, to the best of our knowledge, VQSs are not very commonly used in practice. *Our paper seeks to bridge this gap between current research on VQSs to understand why existing VQSs are not commonly used by analysts and how they can actually be used in practice, as a first step towards the broad adoption of VQSs in data analysis.* In this paper, we present findings from a series of interviews, cognitive walkthroughs, participatory design, and user studies with scientists from three different scientific domains—*astronomy*, *genetics*, and *material science*—through a year-long collaboration. These scientific use cases present a diverse set of goals and datasets that could benefit from a VQS. Our three main research questions are as follows:

*RQ1: What are the challenges in existing scientific data analysis workflows that could be potentially addressed by a VQS?*

Via cognitive walkthroughs and interviews, we gained an understanding of the data analysis workflows presently employed by the scientists, their needs, and the challenges they face. We identified opportunities where a VQS could help accelerate their analysis, by helping them discover insights, gain intuition, or provoke directions for exploration. Finally, we determined the types of research questions and dataset properties that would be most suitable for exploration on VQSs.

*RQ2: What types of interface capabilities are necessary to develop VQSs into a useful component of data analysis?*

Via participatory design, we distilled a set of key features that our scientist participants would need for VQSs to be useful and usable within their data analysis workflows. Based on our early interactions with scientists, we started to build a VQS [33, 34] that, similar to existing VQSs [35], allowed them to search for desired trends via drawing on a canvas. This early system served as a functional prototype for us to engage with scientists further in the participatory design process, understand how they envision themselves using a VQS, and gather feedback on feature designs that could make the VQS more useful. The features we developed address challenges shared across the three scientific domains, ranging from additional querying modalities, to features that support a more integrated workflow, to improving the interpretability of the system output, most of them missing in prior VQSs in the literature. Our collaborative design experience culminated in a full-fledged VQS, *zenvisage*, capable of facilitating rapid hypothesis generation and insight discovery.

*RQ3: How do VQSs accelerate scientific insights? and RQ4: How can VQSs fit within the context of existing data analysis workflows?*

To evaluate our final system *zenvisage*, we conducted a user study with nine scientists (including those who had participated in the design process), all of whom had a vested interest in using a VQS to address their research questions on their datasets. In a 1.5-hour user study, our scientist participants were able to gain novel scientific insights, such as *identifying a star with a transient pattern that was known to harbor a Jupiter-sized planet, finding characteristic gene expression profiles that confirmed the results of a related publication, and learning that the dip in an astronomical light curve is caused by saturated imaging equipment overlooked by the existing error-detection pipeline*. Participants also gained additional insights about their datasets, including debugging mislabelled features and uncovering the erroneous data preprocessing procedure applied to a collaborator’s dataset. We learned how VQSs could be contextualized within scientific data analysis workflows and discovered that VQSs can be used beyond the

exploratory phase of analysis, for data verification, debugging preliminary datasets, and performing sanity-checks on downstream models.

As most existing VQSs are evaluated in a standalone fashion via artificial tasks and datasets, to the best of our knowledge, *our study is the first to holistically examine how VQSs can be used in practice and integrated into existing data analysis workflows*. From these experiences, we advocate common design guidelines and end-user considerations for building the next generation VQSs.

## 2 METHODS

### Background and Motivation

Visual query systems enable users to directly search for visualizations matching certain patterns through an intuitive specification interface. Early work in this space focused on interfaces to search for time series of interest, including TimeSearcher [13, 14], where the query is composed of one or more box constraints, and QuerySketch [35] and Google Correlate [22], where the query is sketched as a pattern. Subsequent work recognized the ambiguity of sketches and improved the expressiveness of sketched queries through finer specification interface and pattern-matching algorithms, including the use of soft constraints [31] and implicit relaxed selection techniques [15]. In addition to this ongoing work, recent work have also performed crowdsourced perceptual studies to understand how humans rank similarity in patterns subjectively [7, 10, 19]. Table 1 summarizes the list of features offered by these existing systems.

While these systems have been shown to be effective for visual querying in controlled lab studies, they have not been evaluated in-situ on real-world use cases. In this work, we adopted a mixed methods research methodology that draws inspiration from ethnographic methods, iterative and participatory design, and controlled studies [18, 21, 24, 29, 32] to more thoroughly understand the design space of VQSs and how various components of VQSs are used in practice. Participatory design has been successfully used in the development of interactive visualization systems in the past [3, 5]. Sedlmair et al. [20] advocate that design study methodology is suitable for use cases in which the data is available for prototyping, but the task is only partially known and the information is partially in the user’s head.

### Participatory Design

Working with researchers from three different scientific research groups, we identified the needs and challenges of scientific data analysis and potential opportunities for VQSs, via interviews and cognitive walkthroughs. We recruited participants by reaching out to research groups via email and word of mouth, who have experienced challenges in dealing with

	Freehand Sketching	Shape Approx.	Range Selection	Flexible Matching	Filter Selection	Group Comparison	Concept Querying	Result Querying	Recommend Result
Timesearcher [13, 14]	Red	Green	Green	Green	Red	Red	Red	Green	Red
QuerySketch [35]	Green	Red	Green	Red	Red	Red	Red	Red	Red
QueryLines [31]	Green	Green	Green	Green	Red	Red	Red	Red	Red
SoftSelect [15]	Green	Green	Red	Red	Red	Red	Red	Red	Red
Google Correlate [22]	Green	Red	Red	Green	Red	Red	Green	Red	Red
TimeSketch [10]	Green	Red	Red	Red	Red	Red	Red	Red	Red
SketchQuery [7]	Green	Green	Red	Green	Red	Red	Red	Green	Red
Qetch [19]	Green	Green	Green	Green	Red	Red	Red	Red	Red
Zenvisage	Green	Green	Green	Green	Green	Green	Green	Green	Green

**Table 1: Table summarizing the key components of VQSs (columns) covered by past systems (row). Green/red cell color indicates whether this feature exist in the system or not. Column header colors blue, orange, yellow represents processes: top-down querying, search with context, and bottom-up querying respectively, described more in Section 5.**

large amounts of data. We initially spoke to analysts from 12 different potential application areas and narrowed down to three use cases in astronomy, genetics, and material science for our participatory design study, based on their suitability for VQS as well as diversity in use cases. Six scientists from three research groups participated in the design of *zenvisage*. On average, participants had more than 8 years of research experience working in their respective fields.

Given our early conversations with participants, we built a basic VQS to serve as the functional prototype in the design study. This early VQS prototype allowed users to sketch a pattern or drag-and-drop an existing visualization as a query, then the system would return visualizations that had the closest Euclidean distance from the queried pattern. The details of the system is described in [33, 34], which focused on the system and scalability aspects of the VQSs.

The use of functional prototypes is common and effective in participatory design to provide a starting point for the participants, as studied by Ciolfi et al.[6]. Our motivation for providing a functional prototype at the beginning of the participatory design sessions is to showcase capabilities of VQSs. Especially since VQSs are not common in the existing workflows of these scientists, participants may not be able to imagine their use cases without a starting point.

During the participatory design process, we collaborated with each of the teams closely with an average of two meetings per month, where we learned about their datasets, objectives, and how VQSs could help address their research questions. A summary timeline of our engagement with the participants and the features inspired by their use cases can be found in Figure 1. Participants provided datasets they were exploring from their domain, whereby they had a vested interest in using a VQS to address their own research questions. Through this process, we identified and incorporated more

than 20 desired features into our VQS prototype, *zenvisage*, over the period of a year.

## Evaluation Study

Visualization systems are often evaluated using controlled studies that measure the user’s performance against an existing visualization baseline [29]. Techniques such as artificially inserting “insights” or setting predefined tasks for example datasets work well for objective tasks, such as debugging data errors [16, 26], but these contrived methods are unsuitable for trying to learn about the types of real-world queries users may want to pose on VQSs. In order to make the evaluation more realistic, at the end of our participatory design study, we opted for a qualitative evaluation where we invited participants to bring datasets that they have vested interests in to address unanswered research questions, in order to study how analysts interact with different VQS components in practice.

The evaluation study participants included the six scientists from participatory design, along with three additional “blank-slate” participants who had never encountered *zenvisage* before. While participatory design subjects actively provided feedback on *zenvisage* with their data, they only saw us demonstrating their requested features and explaining the system to them, rather than actively using the system on their own. So the evaluation study was the first time that all participants used *zenvisage* to explore their datasets.

Participants for the evaluation study were recruited from each of the three aforementioned research groups, as well as domain-specific mailing lists. Prior to the study, we asked the potential participants to fill out a pre-study survey to determine their eligibility. Eligibility criteria included: being an active researcher in the subject area with more than one year of research experience, and having worked on a research project involving data of the same nature as that used in the participatory design. Four of the evaluation studies were

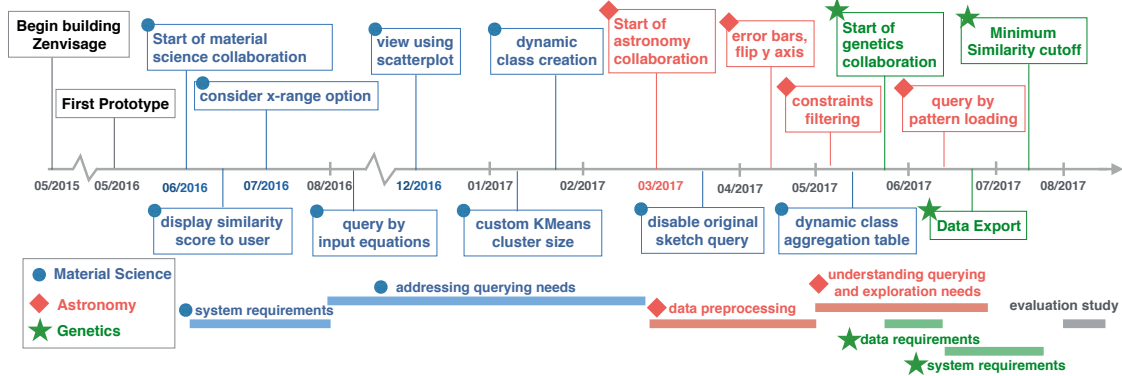


Figure 1: Participatory design timeline for the scientific use cases.

conducted remotely. Participants had the option of exploring their own dataset or an existing dataset that they provided to us during the participatory design process. All three blank-slate participants opted to explore their own datasets.

At the start, participants were provided with an interactive walk-through explaining the system details and given approximately ten minutes to experience a guided exploration of our VQS with a preloaded real-estate example dataset from Zillow [1]. After familiarizing themselves with the tool, we loaded the participant’s dataset and encouraged them to talk-aloud or use external tools as needed during the data exploration phase. If the participant was out of ideas, we suggested one of the ten main functionalities in *zenvisage* that they had not yet used. If any of these operations were not applicable to their specific dataset, they were allowed to skip the operation after having considered how it may or may not be applicable to their workflow. The user study ended after they covered all ten main functionalities. On average, the main exploration phase lasted for 63 minutes. After the study, we asked them open-ended questions about their experience.

### 3 PARTICIPANTS AND DATASETS

During the design study, we observed participants as they conducted a cognitive walkthrough demonstrating their existing data analysis workflow. In this section, we describe our study participants and their use cases to highlight behaviors that participants have adopted for conducting certain analysis tasks.

**Astronomy:** The Dark Energy Survey (DES) is a multi-institution project that surveys 300 million galaxies over 525 nights to study dark energy [9]. The telescope also focuses on smaller patches of the sky on a weekly interval to discover astrophysical transients (objects whose brightness changes dramatically as a function of time), such as supernova explosions or quasars. Their data consist of a large collection of time series brightness observations associated with each object. For over five months, we worked closely with A1, an astronomer on

the project’s data management team working at a supercomputing facility. The scientific goal is to identify a smaller set of potential candidates that may be astrophysical transients in order to study their properties in more detail.

While an experienced astronomer who has examined many transient light curves can often distinguish an interesting transient object from noise by sight, they must visually examine and iterate through large numbers of visualizations of candidate objects. Manual searching is time-consuming and error prone as the large majority of the objects are not astronomical transients. A1 was interested in *zenvisage* as he recognized how specific pattern queries could help scientists directly search for these rare objects.

**Genetics:** Gene expression is a common measurement in genomics obtained via microarray experiments. We worked with a graduate student (G1) and professor (G3) at a research university who were using gene expression data to better understand how genes are related to phenotypes expressed during early development [11, 27]. Their data consist of a collection of gene expression data over time for mouse stem cells aggregated over multiple experiments.

To analyze the data, G1 loads the preprocessed data into a desktop application for visualizing and clustering gene expression data. After setting several system parameters and executing the clustering algorithm, the overlaid time series for each cluster is displayed on the interface. G1 visually inspects that the patterns in each cluster looks “clean” and checks that the number of outlier genes that do not fall into any of the clusters is low. If the number of outliers is high or the clustered visualizations look “unclean”, she reruns the analysis by increasing the number of clusters. When the visualized clusters look “good enough”, G1 exports the cluster patterns to be used as features in their downstream regression tasks.

Prior to the study, G1 and G3 spent over a month attempting to determine the best number of clusters for their upstream analysis based on a series of static visualizations and statistics computed after clustering. While regenerating their results took no more than 15 minutes every time they made a change,

the multi-step, segmented workflow meant that all changes had to be done offline. The team had a vested interest in participating in the design of *zenvisage* as they saw how the interactive nature of VQSs and the ability to query other time series with clustering results could dramatically speed up their collaborative analysis process.

**Material Science:** We collaborated with material scientists at a research university who are working to identify solvents that can improve battery performance and stability. These scientists work with large simulation dataset containing chemical properties for more than 280,000 different solvents. We worked closely with a postdoctoral researcher (M1), professor (M2), and graduate student (M3) for over a year to design a sensible way of exploring their data using VQSs. Each row of their dataset represents a unique solvent, and consists of 25 different chemical attributes. They wanted to use *zenvisage* to identify solvents that not only have similar properties to known solvents but are also more favorable (e.g. cheaper or safer to manufacture). To search for these desired solvents, they need to understand how changes in certain chemical attributes affects other properties under specific conditions.

M1 starts his data exploration process by iteratively applying filters to a list of potential battery solvents using SQL queries. When the remaining list of the solvents is sufficiently small, he examines each solvent in more detail to weigh in the cost and availability to determine experimental feasibility. The scientists were interested in using *zenvisage* as it was impossible for them to uncover hidden relationships between different variables across large number of solvents manually.

## 4 STUDY FINDINGS

### Themes Emerging from Participatory Design

We employed participatory design with our scientists to incorporate key features missing in our original VQS, and unaddressed in their existing workflows. From these discussion and analysis of past VQSs, we identify nine key components of VQSs, described below.

**Exact Shape Specification** interfaces allow users to submit a query through an exact description of a pattern, then the VQS returns a list of most similar matches. Almost all VQS supports freehand sketching for specifying desired patterns (Figure 2a). In addition to sketching, *zenvisage* also allows users to specify a functional form (e.g.  $y=x^2$ ) for a pattern (Figure 2b). This feature was inspired by material scientists who were interested in finding solvents with known analytical models that describes the relationships between their chemical properties.

**Approximate Shape Specification:** While exact shape specification is an intuitive mechanism for constructing a visual query, as pointed out by past works [7, 15], pattern queries can be extremely imprecise. Many interfaces have developed

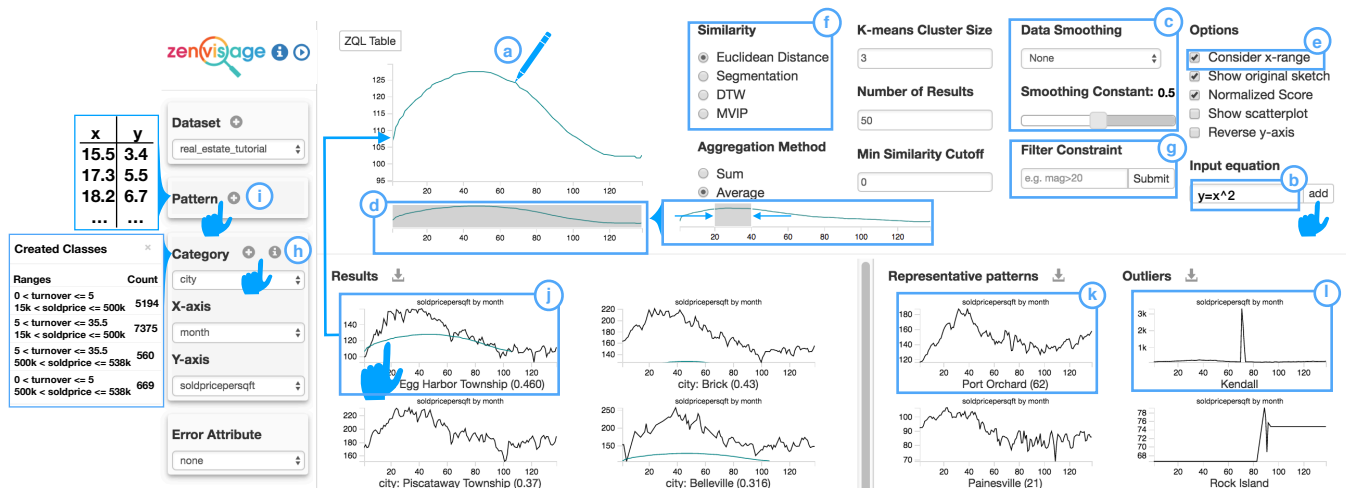
constrained sketching mechanism to allow users to partially specify certain characteristics, such as angular slope queries for specifying the slope of a trend line [14] or piecewise trend querylines over a specified data range [31]. Both Qetch and *zenvisage* supports data smoothing to allow users to interactively change the degree of shape approximation they would like to apply to all visualizations (and consequently for pattern matching). Motivated by the dense and noisy observational data in the astronomy and material science use cases, we developed an interface for users to interactively adjust data smoothing algorithm and parameters on-the-fly to update the resulting visualizations accordingly (Figure 2c).

**Range Selection:** Often in time series analysis there are specific ranges of time and measure values with special domain specific significance that may be of interest to users. One common specification on top of the exact or approximate shape query is limiting the pattern query to be matched only in specific x or y ranges. Range selection can be performed through explicit textbox specification [19, 35], drawing line limits [31], or brushing interactions [13]. *zenvisage* employs the brushing mechanism to select desirable x-ranges to perform shape matching (Figure 2d). Additionally, y axis range selection could be performed through entering a filter constraint on the measure variable.

We chose to support only brushing for x, since it was more common to focus the context based on the independent variable in our use cases, such as zooming into particular sharp dips when looking for planetary transits or anomalous peaks indicative of erroneous experimental measurements. In contrast, y-range selection tends to be more global and enforced across multiple interaction sequences, such as looking for only signals above a certain threshold. The TimeSearcher and Queryline approach is most flexible for range selection as they allow composition of multiple range selection to formulate complex piecewise queries, such as finding a gene expression profile rising from  $x=1-5$  then declining from  $x=5-10$ .

**Flexible Matching:** Studies have shown that to facilitate subjectively meaningful pattern matches, VQSs need to support mechanisms for clarifying sketch interpretation and flexible shape matching algorithms [7, 10, 19]. In *zenvisage*, users has the option to change similarity metrics that perform flexible matching (Figure 2e), as well as the option to ignore the x-range in shape matching (Figure 2f). For finding supernovae, A1 primarily cared about the existence of a peak above a certain amplitude with an appropriate width of the curve, rather than the exact time that the event occurred, leading them to use the consider x-range feature. G1 also expressed that she care about when the “trigger point” as long as the profile is “rising”. This latter features is akin to the temporal invariants in SketchQuery [7].

**Filter Selection:** We find that users with large datasets often need to first use domain knowledge to narrow down their



**Figure 2: Our VQS after participatory design, which includes: the ability to query via (a) a sketch, (b) input equations, (i) drag and drop, or (j) uploaded patterns; (c) preprocessing via data smoothing; query specification mechanisms including (d) x-range selection and filtering, (e) x-range invariance, (g) Filtering, and (h) Dynamic class creation; recommendation of (k) representative and (l) outlier trends. Prior to the participatory design, *zenvisage* only included a single sketch input with no additional options.**

search to a subset of data. This increases their chances of finding an interesting pattern for a given pattern query. To filter data on-the-fly in *zenvisage*, users could compose one or more conditions as filter constraints in a text field (Figure 2g). The filtering can be done on data columns associated with each pattern that is not visualized or on the visualized attributes. This feature is unique to *zenvisage* as most existing VQSs do not allow users to interact with data in the non-visualized columns.

**Group Comparison** addresses a common analytical question from our participatory design where users want to bucket data points into customized classes based on existing properties, and subsequently compare between the customized classes. For example, M1 wanted to create classes of solvents with ionization potential under -10 kJ/mol, over -8 kJ/mol, and ones between that range. Then, he could browse how visualizations involving lithium solvation energy varied across the three classes. To this end, we implemented dynamic class creation, a feature that allows users to use multiple properties to create custom classes on-the-fly, effectively slicing-and-dicing the data based on their needs (Figure 2h). The information regarding the created classes is displayed in the dynamic class information table and as a tooltip over the aggregated visualizations.

**Concept querying:** While input equations are useful when simple analytical models exist, this may not be true for other domains. In these scenarios, users can upload a query pattern of a sequence of points (Figure 2i). This is useful for patterns generated from advanced computational models used for understanding scientific processes or prelabelled data from an external reference database. For example, astronomer A1 can upload a query pattern based on synthetic light curves

generated from simulations or known supernovae that have been discovered in the past. Similarly, Google Correlate allows users to upload their own time series or enter search keywords that corresponds to a time series.

**Result querying** allows users to submit a query based on the results, essentially asking for patterns that are similar to the selected data pattern. TimeSearcher allows users instantiate timebox queries by dragging a result visualization and dropping into the query space; QuerySketch does so similarly through double clicking on the visualization. Similarly in *zenvisage*, users can drag and drop a visualization in either the results pane or the representative and outliers to the query canvas (Figure 2j). The distinction between concept querying and result querying is that concept querying loads in data that are external to the dataset from a reference source, whereas result querying initiates the query using visualizations created from the queried data source.

**Recommendation** displays visualizations that may be of interest to the users based on the context of the data. The recommendation feature is unique to *zenvisage*, which provides visualizations of representative trends based on clustering and highlights outlier instances that looks different from the rest of the visualizations (Figure 2k,l).

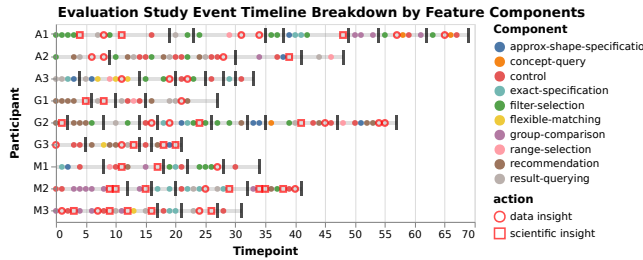
## Evaluation Study Results

We recorded audio, video screen captures, and click-stream logs of the participant's actions during the evaluation study. We analyzed transcriptions of these recordings through open-coding and categorized every event in the user study as either a feature usage or via the coding labels:

- **Insight (Science):** Insight that connected back to the science (e.g. "This cluster resembles a repressed gene.")



- **Insight (Data):** Data-related insights (e.g. “A bug in my data cleaning code generated this peak artifact.”)
- **Provoke (Science):** Interactions or observations made while using the VQS that provoked a scientific hypothesis to be generated.
- **Provoke (Data):** Interactions or observations made while using the VQS that provoked further data actions to continue the investigation.
- **Confusion:** Participants were confused during this part of the analysis.
- **Want:** Additional features that participant wants, which is not currently available on the system.
- **External Tools:** The use of external tools outside of *zen-visage* to complement the analysis process.

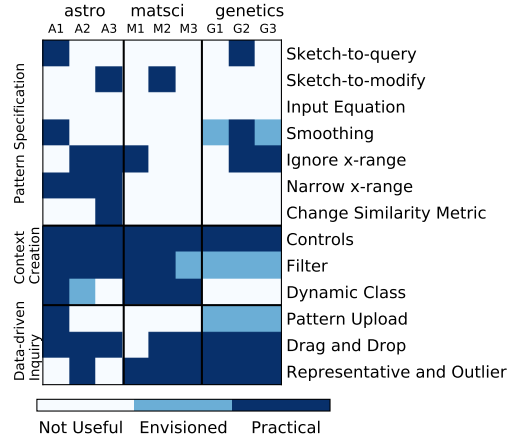


**Figure 3: Timeline of event code and component usage, with every timepoint as an event on the x axis. For clarity, we hide most of the event coding labels other than the insight labels. Black vertical tick indicates a session break, signaling the beginning of a new line of inquiry.**

In Figure 3, we map the features to components based on the taxonomy described in Figure 6 to plot the timeline of event codes and component usage for each participant. As shown in Figure 4, to characterize the usefulness of each feature, we also categorized the features into one of the three usage types based on how each feature was used during the study:

- **Practical:** Features used in a sensible and meaningful way.
- **Envisioned:** Features which could be used practically if the envisioned data was available or if they conducted downstream analysis, but was not performed due to the limited time during the study.
- **Not useful:** Features that are not useful or do not make sense for the participant’s research question and dataset.

We chose to derive these labels from the study transcription to circumvent self-reporting bias, which can often artificially inflate the usefulness of the feature or tool under examination. For the remaining paper, we will focus on understanding the design space of VQSs and highlight the takeaways of our study.

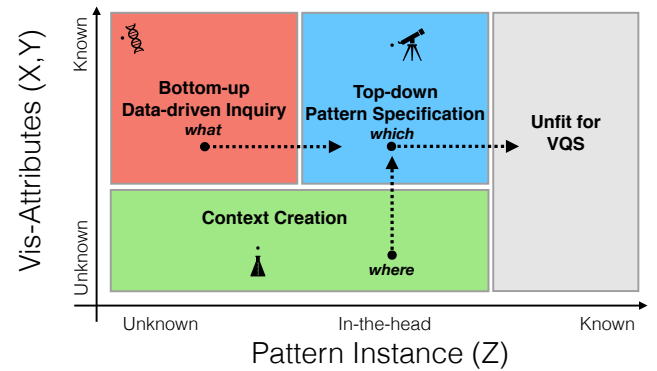


**Figure 4: Heatmap of features categorized as practical usage, envisioned usage, and not useful.**

## 5 DISCUSSION

### Characterizing Design Space for VQSs

Visual querying often consists of searching for a desired visualization instance across a visualization collection ( $Z$ ) for a fixed visualization axes ( $X, Y$ ). To characterize the design space of VQS, we introduce two axes depicting the amount of information known about visualized attribute and pattern instance, as shown in Figure 5.



**Figure 5: The design space of VQSs is characterized by how much the analyst knows about the visualized attributes and pattern instance. Colored areas highlights the three different paradigms of VQSs. While prior work has narrowed the focus of VQSs for use cases solely in the blue region, we envision opportunities for VQSs beyond this to a larger space of use cases and problems covered also by the red and green regions.**

Along the **pattern instance** axis, the visualization instance may already be **known** to the analyst, exist as a pattern **in-the-head** of the analyst, or completely **unknown** to the analyst. For example, if a user wants to study only the pattern related to a specific gene, then the use case is more suited for a visualization-at-a-time system, since the analyst can directly work with the visualization instance without the need for performing visual querying (Figure 5 grey). Inspired by Pirolli and Card’s information foraging framework [28], which distinguishes between information processing tasks that are *top-down* (from theory to data) and *bottom-up* (from data to theory), we define this search-oriented paradigm as “top-down pattern specification” (Figure 5 blue). On the other hand, in the realm of “bottom-up data-driven inquiry” (Figure 5 red), analysts often do not start with a known pattern instance. The pattern of interest is unbeknownst and external to the user and must be driven by recommendations or queries that originate from the data (or equivalently, the visualization). As we will discuss latter, this process is a crucial but understudied topic in past works on VQSs.

The second axis, **visualized attributes**, depicts how much the analyst knows about which X and Y axes she is interested in visualizing. Both the astronomy and genetics use cases, as well as past work in this space, had data in the form of a time series with **known** visualized attributes. In the case of our material science participants, they wanted to explore relationships between different X and Y variables. In the realm of **unknown** attributes, context creation (Figure 5 green) is essential for allowing users to pivot across different visualization subspaces.

## Design Goals and Challenges for VQS Paradigms

In this section, we further explore the design objectives and challenges of each paradigm. We develop a taxonomy for organizing how various features in *zenvisage* fits into the key components and paradigms as shown in Figure 6. In particular, we will describe the main form of inquiry addressed by each paradigm (*what*, *where*, *which*), the characteristic use case, and design challenges involved in building features that support these paradigms.

**Top-down Pattern Specification:** Top-down approaches start with user’s intuition about how their desired patterns should look like based on ‘theory’, including visualizations from past experiences or an abstract conceptions based on external knowledge. The goal of top-down pattern specification is to address the *which* questions in visual sensemaking (*which pattern instance exhibits this pattern?*), effectively moving rightwards to the gray area in Figure 5 where the pattern instance is known.

Based on this preconceived notion of what to search for, the design challenge is to translate the query in the analyst’s head to a query executable by the VQS. As shown in Figure 6,

this includes both components for specifying the pattern as well as controls governing the underlying algorithm of how the shape-matching is performed. For example, A1 knows intuitively what a supernovae pattern looks like and the detailed constraints on the shape, such as the width and height of the peak as well as the level of signal-to-noise tolerance for defining a match. He performs exact specification through sketching, chooses the option to ignore differences on the x axis, and changes the similarity metric for flexible matching. **Bottom-up data-driven inquiry:** While the usage of each querying feature may vary from one participant to the next, generally, result querying and pattern upload are considered bottom-up approaches that go from data to theory by enabling users to query via examples of known visualizations. Bottom-up data-driven inquiries address the *what* questions in the sensemaking process. For example, genetics participants do not have a preconceived knowledge of what to search for in the dataset. They were mostly interested in *what types of patterns exist in the dataset* through representative trends and therefore queried mainly through these recommended results to jumpstart further queries. The goal of data-driven inquiry is to move towards the blue area in Figure 5 where the analyst gains some in-the-head notion of what the pattern looks like. The design challenge of bottom-up approaches includes designing the right set of ‘stimuli’ that could provoke further data-driven inquiries, as well as low-effort mechanisms to search via these results.

**Context Creation:** Analysts often navigate across different parts of the visualization subspace to narrow to a more manageable scope or to explore relationships between different visualization attributes. Context creation addresses the *where* question of sensemaking by enabling analyst to pivot across different visualization collections. The goal is to learn about *where are the patterns of interest?*, effectively moving upwards in Figure 5 along the known attributes region. For example, material scientists often do not start with a pattern in-the-head, but recognize salient trends such as inverse correlation or linear correlation. They switch between different visualized attributes or create different dynamic classes to study their data from different perspectives. The design challenge of context creation is to develop features that serve as ‘lenses’ to navigate users to desired regions of the data, visualize and compare how the data changes between different contexts and ensure that the context is dynamically reflected across other functionalities in the VQSs.

The three paradigm that we have described are not mutually exclusive categories. In fact, we find that participants often construct a central workflow focussed on features from one of the main paradigms and interleave variations with the feature usage from the two other paradigms as they iterate on the analytic task, as shown in Figure 7. As we have seen, the central paradigm adopted by each use case is tightly coupled



Taxonomy of Functionalities in Visual Query Systems

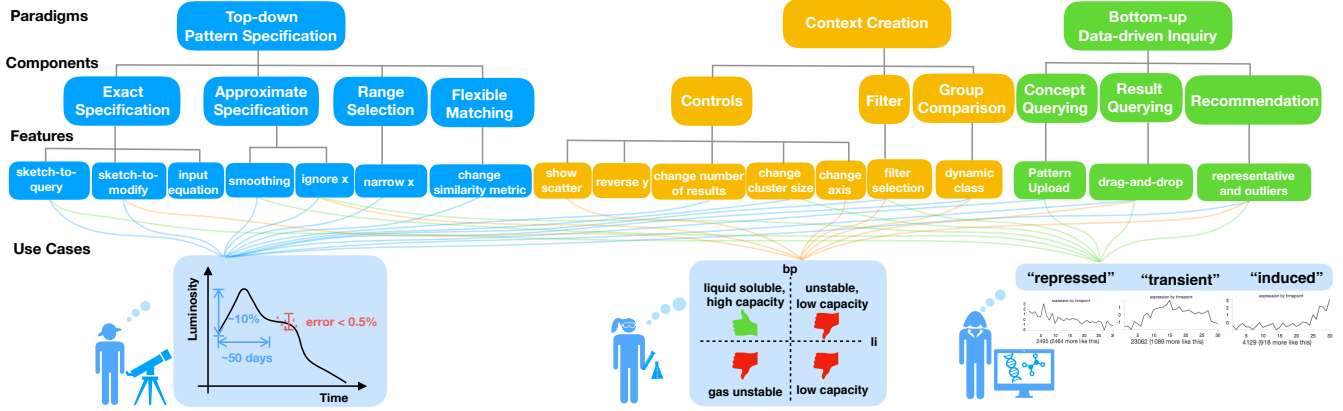


Figure 6: Taxonomy of functionalities in VQSs. From top, each of the three paradigm is broken down into key components in the system, which is instantiated as features in *zenvisage*. The bottom-most layer connects the use cases features that have practical or envisioned usage based on the evaluation study.

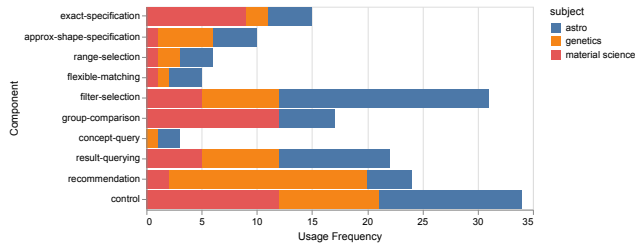


Figure 7: The number of times each component is used during the evaluation study, broken down by subject areas. Astronomers largely focused on filtering, whereas material scientists made heavy use of dynamic class and geneticists made use of recommendations heavily.

with characteristics of the analytic challenges presented by the use cases. Next, we will describe some of the design principles (DP) based on our study findings.

### DP1: The Inefficiency of Sketch

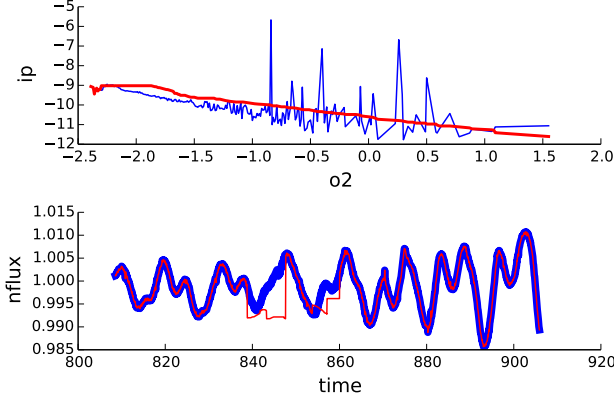
Our interactions with the scientists showed that different modalities for inputting a query can be useful for different problem contexts. To our surprise, despite the prevalence of sketch-to-query systems in literature, only two out of our nine users had a practical usage for querying by sketching.

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 VQS, in which case it made more sense to query using those visualizations as examples directly. In addition, even if a user

has a query pattern in mind, sketch queries can be ambiguous or even impossible to draw by sketching (e.g. A2 looked for a highly-varying signal enveloped by a sinusoidal pattern indicating planetary rotation ).

The latter case is also supported by the unexpected use cases where sketching was simply used as a mechanism to modify dragged-and-dropped queries. As shown in Figure 8 (top), M2 first sketched a pattern to find solvent classes with anticorrelated properties. However, the sketched query did not return visualizations of interest. So, he instead dragged and dropped one of the peripheral visualizations that was close enough to his desired visualization to the sketchpad and then smoothed out the noise due to outlier datapoints by tracing a sketch over the visualization. M2 repeated this workflow twice in separate occurrences during the study and was able to derive insights from the results. Likewise, A3 was interested in pulsating stars characterized by dramatic changes in the amplitudes of the light curves. During the search, hotspots on stellar surfaces often show up as false positives as they also result in dramatic amplitude fluctuations, but happen at a regular intervals. In the VQS, A3 looked for patterns that exhibits amplitude variations, but also some irregularities. As shown in Figure 8 (bottom), she first picked out a regular pattern (suspected star spot), then modified it slightly so that the pattern looks more irregular.

The lack of practical use of top-down pattern specification is also reflected in the fact that querying by equation is unpopular. Both querying mechanism adopt a problematic assumption that analysts start with a known and easy-to-specify search pattern in mind. In both astronomy and genetics use cases, the visualization patterns result from complex physical



**Figure 8: Examples of query modification by M2 (top) and A3 (bottom) performed during the study. The initial drag-and-dropped query is shown in blue and the sketch-modified queries in red.**

processes that could not be written down as an equation analytically. Even in the case of material science when analytical relationships do exist, it is challenging to formulate functional forms in an prescriptive, ad-hoc manner.

Both of these findings suggest that while sketching is an useful analogy for people to express their queries, *the existing ad-hoc, sketch-only model for visualization querying is insufficient without data examples that can help analysts jumpstart their exploration*. Table 1 show that most past work focus on optimizing the components in the top-down paradigm, missing out largely on the key components in the other two paradigms, indicated by the absence of green features on the right hand side of the table. We suspect that the limited coverage in addressing different types of analytics use cases may be why existing sketch-to-query systems are not commonly adopted in practice.

## DP2: Practical Use of Bottom-up approaches

Our results indicate that *bottom-up data-driven inquiries are more common than top-down pattern specification when the users have no desired patterns in mind*, which is commonly the case for exploratory data analysis. Examples of practical uses of result querying includes inspecting the top-most similar visualizations that lie in a cluster and finding visualizations that are similar to an object of interest that exhibits a desired pattern.

Likewise, many participants envisioned use cases for pattern loading. The ability to load in data patterns as a query would enable users to compare visualizations between different experiments, species, or surveys, query with known patterns from an external reference catalog (e.g. important genes of interest, objects labeled as supernovae), or verify

the results of a simulation or downstream analysis by finding similar patterns in their existing dataset. Users can also specify a more precise query that captures the essential shape features of a desired pattern (e.g. amplitude, width of peak), that cannot be precisely sketched. For example, the width of a supernovae light curve is characteristic to the radioactive decay rate of its chemical signature [25], so querying with an exact pattern template would be helpful for distinguishing the patterns of interest from noise.

The prevalence of bottom-up approaches not only point to the need for supporting result querying in VQSs, but also to the need for providing recommendation for users who may not have a desired pattern in mind. We found that geneticists often gain their intuition about the data from the recommended representative trends. One example of rapid insight discovery comes from G2 and G3, who identified that the three representative patterns shown in *zenvisage*—induced genes (profiles with expression levels staying up), repressed genes (started high but went down), and transients (go up and then come down at different time points)—corresponded to the same three groups of genes discussed in a recent publication[11]. The clusters provoked G2 to generate a hypothesis regarding the properties of transients: *“Is that because all the transient groups get clustered together, can I get sharp patterns that rise and ebb at different time points?”* To verify this hypothesis, G2 increased the parameter controlling the number of clusters and noticed that the cluster no longer exhibited the clean, intuitive patterns he had seen earlier. G3 expressed a similar sentiment and proceeded by inspecting the visualizations in the cluster via drag-and-drop. He found a group of genes that all transitioned at the same timestep, while others transitioned at different timesteps. G3 described the process of using VQSs as doing “detective work” that provoked him to generate further scientific hypotheses as well as data actions.

By browsing through the ranked list of result, representative, and outlier in *zenvisage*, participants were also able to gain a peripheral overview of the data and spot anomalies during exploration. For example, A1 spotted time series that were too faint to look like stars after applying a filter constraint of CLASS\_STAR=1. After a series of query results browsing and consultation with an external database, he concluded that the dataset had been incorrectly labelled with all the stars with CLASS\_STAR=0 as 1 during data cleaning. These examples show that both the browsing-act through recommendations and performing search via these results are essential for ‘closing the loop’ between the sensemaking acts in VQSs.

## DP3: Enriching Search with Context

Past studies in taxonomies of visualization tasks have shown that it is important to design features that enable users to select relevant subsets of data in visual analytics[2, 12]. We

found that all participants either envisioned a use case or utilized components of the context creation paradigm offered in *zenvisage* to explore and compare subsets of their data.

A1 expressed that even though the filtering step could be easily done programmatically on the dataset and reloaded into *zenvisage*, filtering on-the-fly was a powerful way to dynamically test his hypothesis. Interactive filtering lowers the barrier between the iterative hypothesize-then-compare cycle, thereby enabling participants to test conditions and tune values that they would not have otherwise modified. During the study, participants used filtering to address questions such as: *Are there more genes similar to a known activator when we subselect only the differentially expressed genes?* `DIFFEXP=1 (G2)` or *Can I find more supernovae candidates if I query only on objects that are bright and classified as a star?* `flux>10 AND CLASS_STAR=1 (A1)`. Three participants had also used filtering as a way to pick out individual objects of interest to query with. For example, G2 set the filter as `gene=9687` and explained that since “this gene is regulated by the estrogen receptor, when we search for other genes that resemble this gene, we can find other genes that are potentially affected by the same factors.”

While filtering enabled users to narrow down to a selected data subset, dynamic class creation enabled users to compare relationships between multiple attributes and between subgroups of data. For example, M2 divided solvents in the database to eight different categories based on voltage properties, state of matter, and viscosity levels, by dynamically setting the cutoff values on the quantitative variables to create these classes. By exploring these custom classes, M2 learned that the relationship between viscosity and lithium solvation energy is independent of whether a solvent belongs to the class of high voltage or low voltage solvents and cited that dynamic class creation was central to learning about this previously-unknown attribute properties:

All this is really possible because of dynamic class creation, so this allows you to bucket your intuition and put that together. [...] I can now bucket things as high voltage stable, liquid stable, viscous, or not viscous and start doing this classification quickly and start to explore trends. [...] And look how quickly we can do it! Quite good!

Context creation enables users to change the lens in which they look through when performing visual querying, thereby creating more opportunities to see the queried data from different perspectives.

## 6 CONCLUSION

## REFERENCES

- [1] 2016. Zillow. <https://www.zillow.com>. Accessed: February 1, 2016.
- [2] Robert Amar, James Eagan, and John Stasko. 2005. Low-level components of analytic activity in information visualization. In *Information Visualization, 2005. INFOVIS 2005. IEEE Symposium on*. IEEE, 111–117. <https://doi.org/10.1109/INFOVIS.2005.24>
- [3] Cecilia R Aragon, Sarah S Poon, Gregory S Aldering, Rollin C Thomas, and Robert Quimby. 2008. Using visual analytics to maintain situation awareness in astrophysics. In *Visual Analytics Science and Technology, 2008. VAST'08. IEEE Symposium on*. IEEE, 27–34. <https://doi.org/10.1088/1742-6596/125/1/012091>
- [4] Austin Nothaft et al. 2015. Rethinking Data-Intensive Science Using Scalable Analytics Systems. *Proceedings of the 2015 ACM SIGMOD International Conference on Management of Data* (2015), 631–646. <https://doi.org/10.1145/2723372.2742787>
- [5] Jason Chuang, Daniel Ramage, Christopher Manning, and Jeffrey Heer. 2012. Interpretation and trust: Designing model-driven visualizations for text analysis. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*. ACM, 443–452. <https://doi.org/10.1145/2207676.2207738>
- [6] Ciolfi et al. 2016. Articulating Co-Design in Museums: Reflections on Two Participatory Processes. *Proceedings of the 19th ACM Conference on Computer-Supported Cooperative Work & Social Computing - CSCW '16* (2016), 13–25. <https://doi.org/10.1145/2818048.2819967>
- [7] Michael Correll and Michael Gleicher. 2016. The semantics of sketch: Flexibility in visual query systems for time series data. In *Visual Analytics Science and Technology (VAST), 2016 IEEE Conference on*. IEEE, 131–140. <https://doi.org/10.1109/VAST.2016.7883519>
- [8] Yuri Demchenko, Paola Grosso, and Peter Membrey. 2013. Addressing Big Data Issues in Scientific Data Infrastructure. *Collaboration Technologies and Systems (CTS), 2013 International Conference on* (pp. 48-55). IEEE. (2013), 48–55. <https://doi.org/10.1109/CTS.2013.6567203>
- [9] Drica Wagner et al. 2017. Dark Energy Survey Year 1 Results: Photometric Data Set for Cosmology. (2017). arXiv:1708.01531
- [10] Philipp Eichmann and Emanuel Zraggen. 2015. Evaluating Subjective Accuracy in Time Series Pattern-Matching Using Human-Annotated Rankings. *Proceedings of the 20th International Conference on Intelligent User Interfaces - IUI '15* (2015), 28–37. <https://doi.org/10.1145/2678025.2701379>
- [11] Brian S. Gloss, Bethany Signal, Seth W. Cheatham, Franziska Gruhl, Dominik C. Kaczorowski, Andrew C. Perkins, and Marcel E. Dinger. 2017. High resolution temporal transcriptomics of mouse embryoid body development reveals complex expression dynamics of coding and noncoding loci. *Scientific Reports* 7, 1 (2017), 6731. <https://doi.org/10.1038/s41598-017-06110-5>
- [12] Jeffrey Heer and Ben Shneiderman. 2012. A taxonomy of tools that support the fluent and flexible use of visualizations. *Interactive Dynamics for Visual Analysis* 10 (2012), 1–26. <https://doi.org/10.1145/2133416.2146416>
- [13] Harry Hochheiser and Ben Shneiderman. 2001. Interactive Exploration of Time Series Data. In *Discovery Science*, Klaus P. Jantke and Ayumi Shinohara (Eds.). Springer Berlin Heidelberg, Berlin, Heidelberg, 441–446.
- [14] Harry Hochheiser and Ben Shneiderman. 2004. Dynamic query tools for time series data sets: Timebox widgets for interactive exploration. *Information Visualization* 3, 1 (2004), 1–18.
- [15] Christian Holz and Steven Feiner. 2009. Relaxed Selection Techniques for Querying Time-series Graphs. In *Proceedings of the 22Nd Annual ACM Symposium on User Interface Software and Technology (UIST '09)*. ACM, New York, NY, USA, 213–222. <https://doi.org/10.1145/1622176.1622217>
- [16] Sean Kandel, Andreas Paepcke, Joseph Hellerstein, and Jeffrey Heer. 2011. Wrangler: Interactive visual specification of data transformation

- scripts. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*. ACM, 3363–3372. <https://doi.org/10.1145/1978942.1979444>
- [17] M Kersten, S Idreos, S Manegold, and E Liarou. 2011. The Researcher’s Guide to the Data Deluge: Querying a Scientific Database in Just a Few Seconds. *Proceedings of the VLDB Endowment*, (2011), 1474. <https://doi.org/10.1145/1409360.1409380>
- [18] Heidi Lam, Enrico Bertini, Petra Isenberg, Catherine Plaisant, and Sheelagh Carpendale. 2012. Empirical studies in information visualization: Seven scenarios. *IEEE Transactions on Visualization and Computer Graphics* 18, 9 (2012), 1520–1536. <https://doi.org/10.1109/TVCG.2011.279>
- [19] Miro Mannino and Azza Abouzied. 2018. Expressive Time Series Querying with Hand-Drawn Scale-Free Sketches. (2018), 1–12. <https://doi.org/10.1145/3173574.3173962>
- [20] Tamara Munzner Michael Sedlmair, Miriah Meyer. 2012. Design Study Methodology: Reflections from the Trenches and the Stacks. 1, 12 (2012), 2431–2440.
- [21] Delbert C. Miller, Neil J. Salkind, and Delbert C. Miller. 2002. *Handbook of research design and social measurement*. SAGE.
- [22] Mohebbi et al. 2011. Google correlate whitepaper. (2011).
- [23] Ivelina Momcheva and Erik Tollerud. 2015. Software use in astronomy: an informal survey. *arXiv preprint arXiv:1507.03989* (2015).
- [24] Michael J. Muller and Sarah Kuhn. 1993. Participatory Design. *Commun. ACM* 36, 6 (June 1993), 24–28. <https://doi.org/10.1145/153571.255960>
- [25] Nugent et al. 1997. Synthetic Spectra of Hydrodynamic Models of Type Ia Supernovae. *The Astrophysical Journal* 485, 2 (1997), 812–819. <https://doi.org/10.1086/304459>
- [26] Patel et al. 2010. Gestalt: integrated support for implementation and analysis in machine learning. In *Proceedings of the 23rd annual ACM symposium on User Interface Software and Technology*. ACM, 37–46. <https://doi.org/10.1145/1866029.1866038>
- [27] Pei Chen Peng and Saurabh Sinha. 2016. Quantitative modeling of gene expression using DNA shape features of binding sites. *Nucleic Acids Research* 44, 13 (2016), e120. <https://doi.org/10.1093/nar/gkw446>
- [28] Peter Pirolli and Stuart Card. 2005. 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. 2–4.
- [29] Catherine Plaisant. 2004. The challenge of information visualization evaluation. In *Proceedings of the Working Conference on Advanced Visual Interfaces*. ACM, 109–116. <https://doi.org/10.1145/989863.989880>
- [30] Prabhu et al. 2011. A Survey of the Practice of Computational Science. In *State of the Practice Reports (SC ’11)*. ACM, New York, NY, USA, Article 19, 12 pages. <https://doi.org/10.1145/2063348.2063374>
- [31] Ryall et al. 2005. Querylines: approximate query for visual browsing. In *CHI’05 Extended Abstracts on Human Factors in Computing Systems*. ACM, 1765–1768. <https://doi.org/10.1145/1056808.1057017>
- [32] Ben Shneiderman and Catherine Plaisant. 2006. Strategies for evaluating information visualization tools: multi-dimensional in-depth long-term case studies. In *Proceedings of the 2006 AVI workshop on BEyond time and errors: novel evaluation methods for information visualization*. ACM, 1–7. <https://doi.org/10.1145/1168149.1168158>
- [33] Tarique Siddiqui, John Lee, Albert Kim, Edward Xue, Chaoran Wang, Yuxuan Zou, Lijin Guo, Changfeng Liu, Xiaofu Yu, Karrie Karahalios, and Aditya Parameswaran. 2017. Fast-Forwarding to Desired Visualizations with zenvisage. (2017). <https://doi.org/10.1145/1235>
- [34] Siddiqui et al. 2016. Effortless data exploration with zenvisage: an expressive and interactive visual analytics system. *Proceedings of the VLDB Endowment* 10, 4 (2016), 457–468. <https://doi.org/10.14778/3025111.3025126>
- [35] Martin Wattenberg. 2001. Sketching a graph to query a time-series database. In *CHI’01 Extended Abstracts on Human factors in Computing Systems*. ACM, 381–382. <https://doi.org/10.1145/634067.634292>