A Programmatic Approach to Applying Visualization Taxonomies to Interaction Logs

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Abstract
Researchers collect large amounts of user interaction data with the goal of mapping user’s workflows and behaviors to their higher-level motivations, intuitions, and goals. Although the visual analytics community has proposed numerous taxonomies to facilitate this mapping process, no formal methods exist for systematically applying these existing theories to user interaction logs. This paper seeks to bridge the gap between visualization task taxonomies and interaction log data by making the taxonomies more actionable for interaction log analysis. To achieve this, we leverage structural parallels between how people express themselves through interactions and language by reformulating existing theories as regular grammars. We represent interactions as terminals within a regular grammar, similar to the role of individual words in a language, and patterns of interactions or non-terminals as regular expressions over these terminals to capture common language patterns. To demonstrate our approach, we generate regular grammars for seven visualization taxonomies and develop code to apply them to three interaction log datasets. In analyzing our results, we find that existing taxonomies at the low-level (i.e., terminals) show mixed results in expressing multiple interaction log datasets, and taxonomies at the high-level (i.e., regular expressions) have limited expressiveness, due to primarily two challenges: inconsistencies in interaction log dataset granularity and structure, and under-expressiveness of certain terminals. Based on our findings, we suggest new research directions for the visualization community for augmenting existing taxonomies, developing new ones, and building better interaction log recording processes to facilitate the data-driven development of user behavior taxonomies.

CCS Concepts
• Theory of computation → Regular languages; Algebraic language theory; • Human-centered computing → Visualization theory, concepts and paradigms;

1 Introduction
A clear understanding of the user’s visual analytic process is critical for designing and evaluating visualization systems. To this end, the visualization community has comprehensively captured their knowledge of users’ visual analytic processes via multiple theoretical frameworks, typologies, and taxonomies [AES05, GZ09, BM13]. We refer to these kinds of structures as taxonomies in this paper. In parallel, researchers are collecting more and more interaction log data to learn how humans analyze information via visualization systems in more data-driven ways [HMSA08, XOW′20, CGL20, PW18]. This interaction log data can reveal the user’s sensemaking process, analytical strategies, and reasoning behavior empirically much like taxonomies have aimed to capture them theoretically. Furthermore, the analysis of interaction log data could “close the loop” by enabling data-driven approaches to testing, validating, and extending longstanding theoretical taxonomies in the visualization community.

However, taxonomies generalize our understanding of user analysis behavior as high-level user goals and strategies, whereas interaction logs aim to capture low-level actions and system events. As a result, inferring high-level goals and analysis strategies from interaction log data often requires an explicit mapping between lower-level interactions captured with the visualization interface and a model of the user’s task. One solution is to manually define user tasks based on the data and visualization system design. For example, Cook et al. [CCI15] defined tasks models such as InvestigateCrime and InvestigateSuspectsBehavior to map low-level data interactions to potential high-level goals. This formulation enabled them to create a mixed-initiative system that infers the user’s task as it evolves throughout their analysis and provides suggestions to aid the process. Similarly, Heer et al. [HMSA08] and Battle and Heer [BH19] categorized their observed actions into task types such as analysis-filter, undo, navigate, as well as interface specific actions like shelf-add, show-me and worksheet-add. Customized categorizations can help researchers reveal patterns in users’ analysis strategies with specific systems, but fail to generalize to other visual interfaces [PW18].

Other works have leveraged existing visualization task taxonomies to systematize the analysis of collected interaction logs. For example, Pohl et al. [PWM′12], Torsney et al. [TWSM17] and Guo et al. [GGZL15] demonstrate the potential of using theoretical taxonomies by mapping interaction logs they gathered to pre-defined task categories. The process first involved selecting the most
appropriate theoretical taxonomy for their collected interaction data then transforming the taxonomy into an actionable task model encoding. All three mapped their application- and task-specific actions to the same set of abstract analytic activities proposed by Yi et al. [YaKSJ07] — select, explore, reconfigure, encode, abstract/elaborate, filter, and connect. Similarly, Kahng et al. [KC20] characterize their collected interaction logs using Gotz and Zhou’s [GZ09] taxonomy. These mappings enabled researchers to verify and compare log analysis methods and determine further stages of system design. Although these existing mappings from logs to taxonomies hold potential for generalizing the log analysis process, there are multiple potential terminals to choose from for such mappings. Furthermore, there is no clear guidance on which theoretical taxonomy to use or how to translate these methods to other interaction log analyses, making it challenging for other researchers to adopt.

In this paper, we seek to bridge the gap between high-level visualization taxonomies and low-level interaction logs programmatically. In this way, we aim to extend the applicability of taxonomies by making them more actionable on interaction log datasets collected from real-world visualization systems. Our approach draws parallels between how users express themselves through interactions with analytic systems and how they express themselves via natural language by reformulating existing visualization taxonomies as regular grammars. We represent user’s recorded interactions as terminals within a regular grammar, similar to the role of individual words in a language, and common sequences of user interactions as non-terminals, which are defined as regular expressions over the terminals. We demonstrate the viability of our approach by generating regular grammars for seven well-known visualization taxonomies (Amar et al. [AES05], Brehmer and Munzner [BM13], Gotz & Zhou [GZ09], Yi et al. [YaKSJ07], Guo et al. [GGZL15], Shneiderman [Shn96], and Gotz & Wen [GW09]) and developing code to apply them to three publicly available interaction log datasets (Battle & Heer [BH19], Liu & Heer [LH14], and Wall [Wal20]). All of our code is provided in our supplemental materials.

To demonstrate the utility of our grammars, we use them to analyze the corresponding taxonomies. Specifically, we derive two new measures for analyzing the expressiveness of visualization taxonomies: coverage and diversity. The coverage-based measure captures the fraction of interaction log events that can be successfully mapped into a given taxonomy. The diversity-based measure examines the frequency and variety of symbols observed after mapping the taxonomy to interaction logs. Understanding these measures for various taxonomies could enable researchers to choose suitable taxonomies for their log analyses.

In analyzing the coverage and diversity of both low-level taxonomies (i.e., terminals) and high-level taxonomies (i.e., non-terminals, regular expressions), we find that existing terminal-level taxonomies show good coverage-based results over the selected interaction log datasets but are skewed in terms of the diversity-based results, resulting in mixed overall expressiveness. Furthermore, non-terminal-level taxonomies have limited expressiveness, primarily due to two challenges: inconsistencies in log granularity and structure and under-expressiveness of specific terminals. We use our findings to highlight the strengths of using existing taxonomies for interaction log analysis and the limitations of their use. Furthermore, we discuss how this framework can be used to enrich theoretical taxonomies and build better interaction logging mechanisms to facilitate actionable and data-driven development of user behavior models.

In summary, we make the following contributions -

- **We reformulate theoretical taxonomies as regular grammars** to make them more actionable for interaction log analysis.
- **We demonstrate our approach by generating regular grammars for seven taxonomies** and developing code to apply them to three real-world interaction log datasets.
- **Based on an analysis of our derived grammars, we suggest new research directions** for augmenting existing taxonomies, developing new ones, and generalizing log recording processes to facilitate data-driven development of user behavior models.

## 2 Background

The visualization community has created a plethora of taxonomies that comprehensively capture a user’s analytic processes. The goal of these taxonomies is to characterize the space of interaction, often by surveying the literature. However, these taxonomies are increasingly being used for log data analysis, a scenario far from the original goal of these taxonomies. The repeated use of taxonomies in log analyses highlights a need for an approach to systematically map low-level user interactions to their corresponding high-level tasks and goals. Below we summarize the literature on visualization taxonomies and their use in log data analysis.

### 2.1 Visualization Taxonomies

Researchers generally view user interactions with visualization systems as a hierarchical construct with multiple levels of granularity, as shown in Figure 1. These granularities are often derived in a bottom-up manner and categorized into four levels, as summarized by Gotz and Zhou [GZ09]: individual user interactions (e.g., [SMG*20]), sequences of user interactions (e.g., [GGZL15]), user tasks (e.g., [BH19]), and high-level reasoning constructs or goals (e.g., [BOZ’14, LTM17]). There exist many visualization taxonomies and applications of these taxonomies at each of these four levels of granularity, which we describe below.

**Individual Interactions.** Taxonomies at the lowest-level categorize the user’s most primitive interactions. Example taxonomies include those proposed by Amar et al. [AES05], Yi et al. [YaKSJ07] and Brehmer and Munzner [BM13]. Amar et al. proposed ten categories of interactions derived from explicit questions asked by students as they visually explored various datasets [AES05]. Yi et al. clustered the interaction capabilities of visualization tools into seven categories of interaction [YaKSJ07]. Brehmer and Munzner used a similar approach to derive a multi-level typology for user interaction [BM13], categorizing not only low-level interactions, but

![Figure 1: User interaction log data is viewed as a hierarchical construct similar to the visualization analytic activity or taxonomy structure proposed by Gotz & Zhou [GZ09].](https://tinyurl.com/regular-grammar-taxonomies)
also the user’s motivations for performing these interactions, such as to present information or to discover new hypotheses.

**Sequences of Interactions.** Low-level interactions are often chained together into sequences or patterns. Taxonomies at this level provide insight into the user’s analysis behaviors and examples of taxonomies include ones proposed by Shneiderman [Shn96], Grammel et al. [GTS10], and Guo et al. [GGZL15]. Shneiderman’s information-seeking mantra: “overview first, zoom and filter, then details on demand” describes an explicit progression of interactions performed when visually exploring data [Shn96]. Grammel et al. conducted a user study to understand how novices construct visualizations in Tableau [GTS10] and used their collected data to tabulate transitions made between attribute and encoding selection interactions. Guo et al. build on their analysis to identify sequences of interactions that frequently lead to insights [GGZL15].

**Tasks.** Related interaction sequences can be clustered together to infer the intent of a user’s analysis, often referred to as tasks. Notable examples at the task level include the taxonomies proposed by Pirolli and Card [PC05], Battle and Heer [BH19], Kang et al. [KGS09], and Alsopah et al. [AZL*18]. Pirolli and Card propose a pipeline of data analysis tasks encompassed within two high-level loops, foraging and sensemaking [PC05]. Battle and Heer [BH19] survey the literature to identify common tasks completed during visual exploration. Kang et al. [KS11], Kandel et al. [KPHH12], and Alsopah et al. [AZL*18] interview industry professionals to summarize common steps and challenges in the data analysis process. Yan et al. segment sequential event logs which combine data, interaction, and user features into high-level user tasks [YGR21]. However, although tasks are richer semantically, they often require in-depth and arguably laborious analysis of the underlying log data to extract meaningful user activities [YGR21].

**Goals and Reasoning.** At the highest-level of the hierarchy, taxonomies aim to capture how the users organize their analysis process into tasks and broader analysis goals. For example, Karer et al. build a formal rule-based model to reason about creation of a visualization and represent the analyst’s information and knowledge flow graphically [KSHL20]. Lam et al. [LTM17] survey design studies aimed to understand how users’ goals are broken down into actionable analysis tasks within visualization tools. Gotz et al. [GZA06] and Shrivinivasan et al. [SVW08] represent analyst’s mental models as links or cycles between insight discovery and knowledge understanding when tracking a user’s interactions with their tools. However, we observe very few works that develop models of the user’s high-level analysis intents. We believe this stems from the challenge of modeling high-level constructs in general. Tasks and analytic reasoning structures at the highest level are difficult to capture but semantically rich as they give insight into human analytic process, while primitive interactions captured at the lowest level of the hierarchy are easier to capture but semantically poor as they provide few details about the human analytic process.

### 2.2 Previous Use of Taxonomies for Interaction Log Analysis

Many works have used taxonomies for interaction log analysis. For example, Guo et al. manually apply the taxonomy proposed by Yi et al. [YaKJS07] to analyze user interaction logs from a text document exploration tool [GGZL15]. Similarly, Satyanarayan et al. [SMW+17] also use Yi et al. [YaKJS07] to define interaction categories to evaluate Vega-Lite. Battle and Heer [BH19] use a similar approach to map analyst’s interactions with Tableau to the Tableau-focused taxonomy of Heer et al. [HMSA08]. Likewise, Gotz and Wen use the interaction taxonomy proposed by Gotz and Zhou [GZ09] as a means for extracting common sequences of visualization interactions [GW09]. Battle and Scheidegger [BS20] use Bremer and Munzner [BM13] to guide literature review on capturing distinctions in how data management technology can be applied in interactive analysis systems. Further, Battle et al. use Pirolli and Card’s sensemaking loop taxonomy [PC05] and also get inspiration in part from Shneiderman’s information-seeking mantra [Shn96] to distinguish common interaction sequences during visual exploration of massive array data [BCS16].

Most of these examples use existing taxonomies to analyze interaction log data, but some also use the taxonomies to evaluate existing systems. In both cases, these applications focus less on using taxonomies for their intended use as design guidelines and more on the unintended use of evaluation. Furthermore, many applications resort to manual mapping of individual log records to taxonomy categories, which can be a tedious process.

### 2.3 Grammar-Based Approaches to Modeling User Behavior

Although few, there have been some interesting works in the visualization community that have taken a language-based or grammar-based perspective to understand user behavior and analytic activity. For instance, several works use Markov models [OGW19,BCS16,RJPL16] and finite automata [DC16] to infer user’s common analysis and exploration behaviors. Dubek et al. in particular derive a grammar-based model to learn user interactions and determine common patterns for guiding new users for their visual analytic process [DC16]. Expressing taxonomies as formal grammars can enable researchers to express theories of user analytic activity using a single, consistent language thereby encouraging a formal means to analyze taxonomies, compare them, and either refine existing taxonomies or derive new ones.

Our goal is to bridge the gap between theoretical taxonomies and data-driven analysis of visualization tools. Specifically, we aim to create a formal and generalized process for applying taxonomies to interaction logs, from which we can generate data-driven guidelines for the design of future taxonomies and visualization tools.

### 3 Our Vision for Reformulating Visualization Taxonomies as Regular Grammars

Inspired by ideas from linguistics and theory of computation, we leverage structural parallels between how people express themselves through interactions with analytic systems and language structure. We reformulate the hierarchical structure of visualization taxonomies (Figure 1) as regular grammars. Low-level user interactions can be represented as individual words in a sentence, i.e., *terminal* symbols within regular grammars. More complex user behaviors captured in higher-levels of the hierarchy (sequences, tasks, goals) can be viewed as *non-terminal* symbols within the regular grammar. We formulate non-terminals as *regular expressions* comprised of terminals and/or other non-terminals. These regular expressions are synonymous with *production rules* which are functions defined over the same terminal and/or non-terminal symbols. In this section, we motivate our approach through a concrete example of generating a regular grammar for a well-known taxonomy.

### 3.1 Defining A Regular Grammar for a Taxonomy

We define a taxonomy $T$ as being at either the low level, i.e., terminal level ($T$), or high level, i.e., non-terminal level ($NT$): $t \in \{T, NT\}$. We use $r$ to define a regular grammar, which consists of three parts:

- a set of terminal symbols $\Sigma$,
- a set of non-terminal symbols $N$, and
– a set of production rules
– Each production rule \( f \) is a function over terminal and/or non-terminal symbols \( f: N \rightarrow \Sigma \cup N \) \(^*\), where \( \Sigma \) denotes the union of two symbol sets and \( * \) denotes repetition of items.

The terminal symbols, \( \Sigma \), are the most primitive building blocks in a grammar, i.e., the lowest level of the visualization taxonomy hierarchy in Figure 1. Therefore, the taxonomies at the lowest level (\( T \)) can be seen as \( \Sigma \). In the context of interaction log data, the set of distinct user interactions captured represent the primitives to be mapped to a target set of terminal symbols, similar to mapping observed words to a target dictionary.

The non-terminal symbols, \( N \), capture the syntax of a grammar. These symbols resemble more complex user analysis behavior captured at higher levels of the visualization hierarchy. For example, recurring patterns or sequences of user interactions within log data can be represented as functions over terminal and non-terminal symbols, akin to deriving common sentence structures from observed word sequences. Thus taxonomies at the higher levels (\( NT \)) can be represented as \( N \). Note that non-terminals are not limited to expressing sequences of terminals and in fact can express all levels of the hierarchy, which we modulate through production rules. In the simplest case, non-terminals can be defined as a mapping to a single terminal, i.e., mapping a single log record to a taxonomy category. In the most complex case, non-terminals can be defined as a function of other non-terminal symbols, i.e., a function of functions. In this way, we can leverage the recursive power of regular grammars to express user analysis behavior at multiple levels of granularity.

3.2 An Example of Generating A Regular Grammar

Here we walk through our approach of generating a regular grammar for two well-known visualization taxonomies: Brehmer and Munzner’s Multi-Level Typology [BM13] (BM) and Shneiderman’s information-seeking mantra [Shn96] (S). Note that we focus on the how level of BM. We also demonstrate its application on an interaction log dataset collected by Wall [Wal20]. This dataset captures user interactions from a visualization system intended to select a committee of politicians, enabling further study of the user’s potential biases in decision making. We represent our approach in Figure 2.

Brehmer and Munzner classify individual interactions into 11 categories, which we represent as a set of terminal symbols \( \Sigma_{BM} \):

\[
\Sigma_{BM} = \{\text{annotate, import, derive, record}, \text{aggregate, select, navigate, arrange, change, filter}\}
\]

Note that we can represent any low-level visualization taxonomy as a set of terminal symbols in a similar fashion.

The Wall dataset has 11 distinct log record categories representing individual interaction types, all of which can be represented using an equivalent terminal from \( \Sigma_{BM} \). As shown in Figure 2(1), examples of these log records include mouseover from list, change attribute distribution, filter changed, etc., which allow users to retrieve details for specific politicians within the current committee list, change the rendered distribution measures computed over the politician attributes, and change the politician filtering criteria, respectively. These distinct log records can be mapped to corresponding terminals in \( \Sigma_{BM} \) using production rules defined over the Wall dataset \( D_W \rightarrow \Sigma_{BM} \), which we label as wall2020-brehmermunzner2013-mapping (Figure 2(2)). For example, we can use these functions to map the individual log records listed earlier to select, aggregate, and filter terminals in \( \Sigma_{BM} \) (Figure 2(3)).

High-level taxonomies such as Shneiderman’s information-seeking mantra (‘overview first, zoom and filter, then details-on-demand’) [Shn96] express common sequences of user interactions observed during visual exploration. The components of this mantra (‘overview’, ‘zoom’, ‘filter’ and ‘details-on-demand’) can together be represented as a set of non-terminal symbols \( N_S \) (see Figure 2(4)): \( N_S = \{\text{overview, zoom, filter, details_on_demand}\} \)

Other high-level taxonomies can also be represented using non-terminal symbols in a similar fashion.

Each non-terminal in \( N_S \) can be defined as a function of one or more Brehmer and Munzner terminals: \( N_S \rightarrow \Sigma_{BM} \) (Figure 2(5)). For example, the overview non-terminal symbol occurs when users transform the data, arrange the data differently or visualize the data in various ways. These transformations can be represented using the aggregate, arrange or encode terminals in \( \Sigma_{BM} \). The corresponding production rule is as follows, defined as a regular expression:

\[
\text{overview} \rightarrow (\text{aggregate}|\text{arrange}|\text{encode})^+
\]

Similarly, the zoom, filter and details-on-demand non-terminal symbols can be defined as regular expressions over \( \Sigma_{BM} \):

\[
\text{zoom} \rightarrow (\text{navigate})^+ \\
\text{filter} \rightarrow (\text{filter})^+ \\
\text{details_on_demand} \rightarrow (\text{select}|\text{derive})^+
\]

We label these production rules as brehmermunzner2013-shneiderman1996-mapping. Similar production rules can be generated for the same non-terminal using different underlying terminals, e.g., terminals defined by Yi et al. [YaKS07] instead of Brehmer and Munzner [BM13].

Since production rules can be represented as regular expressions, we can easily apply them to user interaction sequences within logged analysis sessions to determine whether relevant patterns arise within this data. For example, Figure 2(6) shows one occurrence of the information-seeking mantra in the user session data. Similarly, other non-terminals represented by their corresponding production rules can be used to examine patterns in user interaction log data.

4 Approach

Here, we demonstrate our entire approach of formulating the regular grammar and applying it to interaction log data in more details. We first map low-level interaction log records to the low-level
We select the three representative high-level taxonomies selected are: (e.g., GAN Lab [KC20]) or evaluation (e.g., Sliceplorer [TWSM17])

Eurographics Conference on Visualization (EuroVis) (2022 submitted to at least 60% distinct categories of the representative taxonomies.

In order to develop our approach, we select representative analytic visualization taxonomies and interaction log datasets which we describe first before elaborating on our approach.

4.1 Representative Analytic Visualization Taxonomies

We select seven taxonomies: four taxonomies occurring at the lower granularity of the hierarchical structure and three taxonomies occurring at the higher granularity as representative taxonomies on which we demonstrate the generation of regular grammar. The representative taxonomies are selected based on two factors. First, we look for the implementation and application of the taxonomies in application systems to demonstrate their empirical use. We use the number of citations measure, with a minimum threshold of 300 as a quantitative measure of the widespread of the taxonomies. Second, we examine the feasibility of taxonomies such that they have enough detail to be mapped to interaction log data in order to successfully generate a regular grammar for it. We observe the number of systems that apply or use these taxonomies for either their design, analysis (e.g., GAN Lab [KC20]) or evaluation (e.g., Sliceplorer [TWSM17]) as a measure of feasibility of the taxonomies. In accordance to these factors, the four representative low-level taxonomies selected are:

[T1] Amar et al.'s [AES05] analytic task taxonomy.
[T2] Brehmer and Munzner's [BM13] multi-level typology of visualization tasks.
[T3] Gotz and Zhou's [GZ09] characterization of visual activity.
[T4] Yi et al.'s [YaKSJ07] interaction technique category.

And, the three representative high-level taxonomies selected are:

[NT1] Shneiderman's [Shn96] information-seeking mantra.
[NT2] Gotz and Wen's [GW09] behavior patterns to infer user’s intended visual task.
[NT3] Guo et al.'s [GGZL15] common analysis patterns.

And the two researchers discussing the conflicting mappings and reasoning on their choices. This discussion led to a total of 12 = 3 interaction log datasets (D) × 4 terminal taxonomies (ΣF) unique mappings.

Process. We follow a qualitative coding process to develop a code-book of these mappings. We followed a three step iterative approach to establish the final code-book of the mappings for all the terminal taxonomy and interaction log dataset pairs.

In the first iteration, for each interaction log dataset, two researchers on the project individually used the elimination approach [Smi43] to map each distinct log record d ∈ D to its corresponding terminal symbol i ∈ Σ, producing the mapping f : D → Σ. For example, suppose the dragging of a slider is being mapped to the Brehmer and Munzner terminal, represented by ΣBM (see subsection 3.2), f may map this recorded event to the filter terminal ∈ ΣBM. We develop functions over Σ and the interaction log dataset D which we call mappings. These mappings are formulated as JSON objects, one for every interaction log dataset and low-level taxonomy that is a terminal symbol (Σ). The individual user interactions in an interaction log dataset can be synonymous to low-level taxonomy categories, that is terminal symbols (Σ).

Overview. Therefore, for a given interaction log dataset D and terminal symbol Σ, we can translate each log record d ∈ D to its corresponding terminal symbol i ∈ Σ, producing the mapping f : D → Σ. This was repeated for all four terminal symbol taxonomies. The two researchers mapped an interaction log record to a special null terminal if they found multiple or no terminals from the taxonomy that mapped to the log record. At the end of the first iteration, the mappings of both the researchers were aligned to calculate an inter-coder reliability score of 0.47. In order to reconcile on the code-book, the second iteration constituted of both the researchers discussing the conflicting mappings and reasoning on their choices. This discussion led to a consensus on the mappings or finalizing the conflicts. The second iteration of forming the code-book resolved majority of the conflicts and increased the inter-coder reliability score to 0.91. In the final round of iteration, the final conflicts were resolved by having...
the other two researchers on the project follow the same process which further raised the inter-coder reliability score to 0.99.

Eventually, the special **null** terminal was used for interaction log records that couldn’t be mapped to a single terminal even after discussions with all four researchers. Examples of such terminals are the log records for resetting of the interface, which are commonly observed in the Tableau tool and thus in Battle and Heer’s [BH19] interaction log dataset. The Gotz and Zhou [GZ09] taxonomy omits any interaction category that resets interfaces, as a result, we set all log records that correspond to resetting the interface to **null** when mapping to the Gotz and Zhou terminal symbol $\Sigma_{GZ}$.

We use this final iterated and established code-book of mappings to perform further analysis. A justification for each mapping is provided as an additional nested description property in the JSON object mappings explaining our reasoning process. Along with the mappings, we provide a Python script that takes as input a interaction log dataset file ($D$) and the terminal symbol mapping ($\Sigma$) and outputs another file containing a list of corresponding terminal symbols, $i \in \Sigma$ of all log records of the interaction log dataset, $d \in D$.

### 4.4 Non-terminal Symbols ($N$)

The user patterns or sequences observed in interaction log datasets can be synonymous to high-level sequence taxonomy categories, that is non-terminal symbols ($N$). Therefore, we represent every high-level taxonomy describing user’s sequences ($NT$) as a distinct set of non-terminal symbols, $NT$.

**Overview.** Each pattern or sequence in high-level taxonomy can be represented as consecutive interactions of simpler symbols, which are terminals ($\Sigma_T$). Therefore, we simply degenerate each pattern into simpler terminals as assign them to included in the set of non-terminal symbols. These degenerations are either explicitly provided by the researchers who find these patterns or are described by them in words. Thus, based on these explicit representations or descriptions, we come up with a set of consecutive simpler terminals, $r \in NT$ that express the non-terminal sequence. Therefore, we develop a total of $3 \times 3$ non-terminal symbols ($NT$) unique mappings constituting of the terminal symbols ($\Sigma$).

**Process.** We follow a similar iterative and qualitative process to establish the code-book for the non-terminal symbols mappings as followed for the terminal symbols.

In the first iteration, two researchers on the project understand the descriptions of the researchers coming up with the sequences to build the set of non-terminal symbols. This is repeated for all three representative non-terminal taxonomies ($NT$). A full inter-coder reliability score of 1 was achieved after the first iteration, thereby, saving further discussion and iterations. Once again, this iterated and established code-book of regular expressions mappings was used to perform further analysis.

### 4.5 Production Rules

Empirically in interaction log datasets, complex behaviors of users are perceived to be patterns of underlying simpler interactions. In regular grammar, this can be paralleled to forming non-terminal symbols ($N$) using combinations of simpler terminal symbols ($\Sigma$) put together. Even more complex sequences, which speak to the more abstract tasks of the user can be formulated as combinations of not only the terminal symbols but also non-terminal symbols. Our approach adopts this approach by the ability to generate production rules over non-terminal symbols. Production rules can be functions or regular expressions of both terminal and non-terminal symbols to generate complex non-terminal symbols thus informing user’s common behaviors as sequences or tasks in interaction log datasets.

**Overview.** Each non-terminal can be represented as a function of terminal symbols, $\Sigma_T$. Because each low-level taxonomy or terminal symbol has a unique mapping represented by $\Sigma$, the same high-level taxonomy may be generated using different terminals, depending on which underlying low-level terminal is used. Thus, we develop functions or mappings of all possible pairings of low-level taxonomy (i.e., terminals) and high-level taxonomy (i.e., non-terminals) listed in section 3. These mappings too are formulated as a JSON objects, one for every terminal and non-terminal pair. Therefore, we develop a total of $12 \times 4$ terminal symbols ($\Sigma_T$) $\times 3$ non-terminal symbols ($NT$) unique mappings.

**Process.** We follow a similar iterative and qualitative process to establish the code-book for the non-terminal symbols mappings as followed for the terminal symbols.

The mappings for non-terminal symbols are produced by building functions of mapping each individual non-terminal of the non-terminal sequence to its corresponding terminal mapping. This is repeated for all non-terminal taxonomy and terminal-taxonomy pairs. After the first iteration, where two researchers on the project individually produced the mappings for the non-terminals, a inter-coder reliability score of 0.73 was achieved. After a second iteration of discussion and resolving conflicts, a full inter-coder reliability score of 1 was achieved, thereby, saving a third iteration. Once again, this final iterated and established code-book of regular expressions mappings was used to perform further analysis.

For some non-terminals additional information about the attributes and dimensions on which interactions were captured had to be taken into account. For example, two non-terminals observed by Gotz and Wen [GW09]: scan and drill-down mean that users iteratively perform the inspect interactions over a series of similar (i.e., on the same dimension or attribute) and different (i.e., on different dimensions or attributes) visual data objects respectively. To meet these needs, we modified the underlying terminal symbols to include inspect same and inspect different for scan and drill-down respectively.

Similar to the previous mappings, regular expressions also used the special **null** category if the non-terminals cannot be represented as regular expressions using underlying terminals. For instance, scan and drill-down Gotz and Wen non-terminals cannot be represented with Amar et al. [AES05] terminal, since there is no inspect-like interaction in Amar et al. taxonomy. We also provide another Python script that takes as input the terminal mappings file ($\Sigma$) and non-terminal mappings file ($NT$), and outputs another file containing a list of sequences found.

## 5 Analysis

A natural question stemming from this work is: what can we learn from translating taxonomies into regular grammars? To answer this question, we applied our derived grammars to three different interaction log datasets, and used the results to evaluate the corresponding taxonomies. Our objective is to identify measurable differences between grammars that may reveal the most suitable taxonomies for a given analysis context.

Using prior work in evaluating visual encoding grammars as inspiration [SMWH17, Mac86], we focus on measuring the
expressiveness of taxonomies in our analysis. Based on our review of the literature (see section 2), we propose two measures of expressiveness for visualization taxonomies: coverage and diversity. When choosing taxonomies for their log analyses, we find that researchers tended to favor taxonomies where all distinct log records could be mapped to a terminal within the taxonomy, i.e., taxonomies that generate mappings with high coverage of all log records. In response, our proposed coverage measure calculates the fraction of interaction log records that can successfully be mapped to the symbols of a given taxonomy. Similarly, researchers also seemed to favor taxonomies that would avoid mapping many different log records to the same taxonomy category. For instance, if every log record maps to a single terminal, then it becomes impossible to extract meaningful interaction sequences or patterns. To this end, our diversity measure captures the frequency and variety of symbols observed after mapping a taxonomy to the interaction log data.

5.1 Analyzing the Expressiveness of Terminal Taxonomies

Before we can extract patterns from log data, we first need to map it to a relevant set of terminals (Σ). However, the expressiveness of a terminal-level taxonomy can influence our ability to extract patterns, such as by having low coverage that causes us to lose data records, or by having low diversity that causes us to lose semantic meaning across interaction sequences. To evaluate the expressiveness of terminal-level taxonomies, we analyze the coverage they provide when mapped to each of our three datasets, as well as the diversity of terminals observed across the resulting mappings. We evaluate four different terminal-level taxonomies in this analysis, those for: Amar et al. [AES05], Brehmer and Munzner [BM13], Gotz and Zhou [GZ09], and Yi et al. [YaKSJ07].

5.1.1 Coverage-based Analysis

For each terminal-level taxonomy (see section 3), we map each distinct log record from our datasets to its corresponding terminal symbol. To measure coverage, we calculate the percentage of successfully mapped interaction log records or the percentage of “non-null” mappings for each interaction log dataset and taxonomy pairing.

Table 2 reports our findings. We observe relatively high coverage for two out of three datasets: 100% coverage of the Wall dataset, 85-100% coverage of the Liu & Heer dataset, and 46-68% coverage of the Battle & Heer dataset. We find that the Brehmer and Munzner taxonomy [BM13] provides the best coverage across all three datasets, followed by the taxonomy of Gotz and Zhou [GZ09]. The Amar et al. taxonomy [AES05] provided the lowest coverage, 65.56% on average.

| Taxonomy                  | Battle & Heer | Liu & Heer | Wall | Avg.  |
|---------------------------|---------------|------------|------|------|
| Amar et al. [AES05]       | 46.67%        | 50%        | 100% | 65.56% |
| Brehmer & Munzner [BM13]  | 68.89%        | 100%       | 100% | 89.63% |
| Gotz & Zhou [GZ09]        | 67.78%        | 100%       | 100% | 89.26% |
| Yi et al. [YaKSJ07]       | 74.44%        | 91.67%     | 100% | 88.7% |
| Avg.                      | 64.45%        | 85.42%     | 100% |      |

Number of terminals alone did not seem to be a strong predictor of coverage. For example, Brehmer and Munzner propose fewer terminals than Gotz and Zhou but the Brehmer and Munzner taxonomy provides (slightly) higher coverage. Amar et al. propose fewer terminals as well, but their taxonomy provides lower coverage. Instead, we see a consistent difference in coverage based on dataset, suggesting that coverage is inversely proportional to the complexity of the visualization systems used to capture the interaction logs. For instance, the Wall dataset was collected using a streamlined interface with fewer features, leading to high coverage, while the Battle and Heer dataset was captured using the feature-rich Tableau Desktop tool, resulting in the lowest observed coverage. Thus existing taxonomies seem to provide high coverage for streamlined interfaces but not necessarily more complex tools. Nonetheless, we reiterate that we still observe generally high coverage for the terminal taxonomies, indicating that this aspect of expressiveness is well-supported at the terminal level.

5.1.2 Diversity-based Analysis

To measure the diversity of terminal-level taxonomies, we analyze the distribution of terminals observed for each interaction log dataset. Specifically, we evaluate the percentage of log records mapped to each terminal within a taxonomy to measure terminal utilization, as well as the fraction of the dataset mapped to the most popular terminal to gauge redundancies in the resulting mappings. We represent these distributions in Figure 3 as four stacked bar charts, one chart per taxonomy. Each stack represents a log dataset, and each bar an individual terminal symbol from the corresponding terminal taxonomy.

Terminal Under-Utilization. First, we consider under-utilization of terminals, which can help us understand which taxonomies may contain terminals that do not provide meaningful context for log analyses. We find that across the four terminal-level taxonomies evaluated, only two had obvious under-utilized terminals. Across all three log datasets, the Amar et al. taxonomy had two terminals that were never used: find anomalies and find extremum. Similarly, across all three log datasets, the Gotz and Zhou taxonomy had three terminals that were never used: restore, split, and bookmark.

Terminal Over-Utilization. Next, we consider over-utilization of terminals, which can help us determine when we may be losing semantic meaning across consecutive interactions. For example, if three consecutive but different interactions all mapped to the exact same terminal, we effectively lose the meaning behind these interactions—and as a consequence, the sequences derived from these interactions—in later analyses. To measure this, we identify the most popular terminal for a given log dataset and taxonomy pairing and calculate the percentage of log records mapped to this terminal. For the Battle and Heer dataset, we find that the Brehmer and Munzner taxonomy had the highest measure of 95.43% (for the aggregate terminal), and Gotz and Zhou had the highest measure of 94.95% (for the remove terminal). For the Liu & Heer dataset, the Amar et al. taxonomy had the lowest measure of 86.99% (for the filter terminal), and the Yi et al. taxonomy had the highest measure of 95.43% (for the explore terminal). For the Wall dataset, the Brehmer and Munzner taxonomy had the lowest measure of 47.86% (for the navigate terminal), whereas the Gotz and Zhou taxonomy and Yi et al. taxonomy tied for the highest measure of 81.61% (for the inspect and explore terminals, respectively). Overall, we found that the Brehmer and Munzner taxonomy provided the best measures. We also stress that a measure of 95.43% means that the overwhelming majority of log records were mapped to the exact same terminal,
which likely will not lead to a meaningful analysis of interaction sequences, since most interaction events will appear to be identical.

We acknowledge that since none of these taxonomies were designed to analyze the specific logs we used, there are likely dataset effects that come to play in our analysis. For example, we found that terminal over-utilization was consistently high for all of our taxonomies when analyzing the Liu & Heer and Wall datasets, but not for the Battle & Heer dataset. These findings suggest that some log datasets may not be as complex as others, likely because the original interfaces themselves contained proportionally fewer features, e.g., the research prototypes developed by Liu & Heer and Wall versus Tableau Desktop, the tool used by Battle & Heer. That being said, we do still observe differences between taxonomies even when dataset differences are taken into effect, with the Brehmer and Munzner taxonomy providing overall the best over- and under-utilization results. From these skewed findings of terminals across the interaction log datasets, the diversity-based measure of expressiveness is poor. Since, the coverage-based measure is good and the diversity-based measure is poor, the terminal taxonomies show a mixed expressiveness when applied on interaction log data.

5.2 Analyzing the Expressiveness of Non-Terminal Taxonomies

Similar to the analysis performed for terminal symbols, the coverage-based analysis of non-terminal symbols is analyzed by calculating the number of occurrences of established sequences or non-terminals in the interaction log datasets. And, the diversity-based analysis of non-terminal symbols is informed by finding new sequences or new non-terminals that are observed within and across interaction log datasets.

5.2.1 Coverage-based Analysis

Likewise to the coverage of terminal symbols, we calculate the coverage of non-terminal sequences observed in the interaction log datasets. The non-terminal symbols are sequences of interactions or patterns that recur within user analysis sessions, and can be represented using simpler terminal symbols. Since, we develop regular grammars for four terminal symbols, we use all of them to represent the non-terminal sequences individually. While calculating the number of non-terminals in the interaction log datasets, we observed multiple user sessions having consecutive log records that mapped to the same terminals. Since, having a sequence of similar terminals makes the chain of user terminals mappings very long and verbose for analysis, we...
use the “collapse approach” to collapse consecutive similar terminal symbols to one, as shown in Figure 4 (a). The sequence of eight terminals are reduced to five terminals after applying the collapse approach on the filter and select repetitive terminals. We use the regular expressions generated for each of the non-terminal symbols to sum the number of sequences observed for each of the user sessions in the interaction log datasets. We report these in Table 3 where we represent the average number of non-terminal sequences observed per user session with a confidence interval of ±95%. For instance, we observe an average of 2.25 ± 0.55 = 1.7 to 2.8, which is approximately 2 to 3 number of elaborating Guo et al. [GGZL15] non-terminal sequences that are expressed using the Gotz and Zhou [GZ09] underlying terminals in one user session of the Battle and Heer [BH19] interaction log dataset.

In general, we observe that the coverage of non-terminal symbols is less than that of the terminal symbols. Of the representative non-terminal taxonomies, we observe the least coverage for the Guo et al. [GGZL15] non-terminals (maximum low counts of sequences), followed by Shneiderman’s [Shn96] information-seeking mantra as we rarely observe any of the sequences in user sessions. On the other hand, the Gotz and Wen [GZ09] non-terminal sequences seem to be more widely observed across user sessions. We attribute this behavior to the environments and tools used to come up with these non-terminals. For instance, since Guo et al. [GGZL15] realized the common user sequences only using a single and specific text analysis tool, we tend to not observe them in any other datasets. Although the information-seeking mantra is widely known as a design guideline and user analysis pattern, we barely observe its occurrence, especially in the more feature rich Tableau tool (Battle and Heer interaction log dataset). The Gotz and Wen non-terminals seem to be the most prevalent across the interaction log datasets, making them more generalizable for multi-system and multi-task purposes.

5.2.2 Diversity-based Analysis

Various researchers have used graph structures and algorithms to observe common patterns in user’s behavior and come up with the non-terminals. We use our regular grammars approach to find new common behaviors of users within and across the interaction log datasets.

First, we aim to find common sequences of terminals performed across all participants within each interaction log datasets, that is the common sequences that every user may have performed during their analysis session. This analysis provides insight into the common behaviors of users when they perform the same analysis. We use terminal mappings of individual taxonomies and split them per user sessions. They we find intersection of consecutive sequence of terminals to attain the common sequences within the user sessions of an interaction log dataset. Similar to the previous analysis where we used the “collapse” approach to reduce the vast amounts of log data collected, we use the “plus” and “numeric” approach for this analysis, as shown in Figure 4. In the plus approach, consecutive similar terminal symbols are collapsed to one terminal symbol concatenated with a “+” notation. For example, the consecutive filter and select terminals are replaced with filter+ and select+ terminals respectively, as seen in Figure 4. The numeric approach is similar to the plus approach but the plus notation is instead replaced with the number of times the terminal is repeated consecutively. Again as observed in Figure 4, the two consecutive filter terminals and three consecutive select terminals are replaced with filter2 and select3 respectively. We favor the plus and numeric approaches instead of the collapse approach for this analysis since the former approaches preserve the interactions of the users.

The new non-terminal sequences observed for the interaction log datasets with different underlying terminal symbols are denoted in Table 4. For Battle and Heer interaction log dataset, we do not observe any common sequences across user sessions for any underlying terminal symbols. For both Liu and Heer and Wall interaction log datasets, we observe different common non-terminal sequences for different underlying terminal symbols as seen in the table. Most of these sequences follow the same pattern of alternating simpler terminals and non-terminals. For instance, the Wall interaction log dataset shows the alternating pattern of multiple retrieve-value and a filter terminals followed by a retrieve-value terminal as seen in the plus approach using the Amar et al. underlying terminals. A similar pattern occurs with multiple brush and a delete terminals followed by a brush terminal in the Liu and Heer interaction log dataset with the Brehmer and Munzner underlying terminals. However, since we don’t see the exact pattern match for the plus and numeric approaches of the use cases, we can conclude that even though each of the users in a dataset perform similar patterns, they take different number of interactions (or terminals) within the patterns.

Further, we extended this analysis to find common sequences across the interaction log datasets, but we do not see any common user sequences across the datasets. Therefore, the expressiveness of the non-terminals at both the diversity and coverage measures.

6 Discussion

From our analysis, we find that overall, existing terminal-level taxonomies have mixed expressiveness as defined by the coverage and diversity of the mapped terminals. Across all the three interaction log datasets analyzed, we observe high coverage for our representative terminal taxonomies, suggesting that the current set of low-level taxonomies in the literature provide sufficient coverage of log records.
within real-world interaction log datasets. However, we find that some of the representative terminal taxonomies tend to under- or over-utilize certain terminals, resulting in skewed distributions of emitted terminals within our mappings and thus limited diversity.

We believe these mixed results stem from the tension between optimizing for specificity, or ensuring specific user activities are represented, and generality, or designing terminals that can be applied to many tools, when designing taxonomies. On the one hand, our findings demonstrate the utility of theoretical taxonomies beyond their intended use as descriptive tools for designers. Our grammar-based approach reveals how taxonomies can be useful tools for analyzing interaction logs from a variety of systems. On the other hand, our approach demonstrates the limitations of taxonomies. For example, our results suggest that skewed taxonomies may be too general, sacrifice context, and as a result lead to mappings that may not be meaningful for interaction log analysis. In some cases, these taxonomies produced a single terminal for most (e.g., over 95% of) log records, resulting in homogeneous mappings. However, striving purely for specificity may also produce taxonomies with limited applicability, e.g., taxonomies that apply only to one tool. Our research highlights a potential need for more taxonomies that strike a balance between specificity and generality. It also suggests a potential direction for achieving this balance: augmenting taxonomies to include critical contextual cues as input to the underlying regular grammar; for example, details about the system wherein the interactions are being performed.

Based on our analysis of observed interaction sequences, we rarely observe the regular expressions proposed in existing non-terminal taxonomies. Furthermore, the few patterns we do observe represent a small fraction of the log datasets analyzed. Although existing taxonomies do not directly match the interaction log datasets we analyzed, our regular grammars approach enables deducing new data-driven taxonomies at higher levels of user activity such as interaction sequences and analysis tasks. For example, our analysis approach reveals common sub-sequences within interaction log datasets which represent more meaningful and complex patterns than those proposed in current taxonomies. Finally, we do not observe any common sequences that occur across all interaction log datasets. We believe these issues stem in part from a mismatch between current non-terminal taxonomies and log recording strategies, as well as challenges originating from the terminal rather than non-terminal level: over- and under-utilization of certain terminals and lack of important contextual cues in taxonomies.

### Table 4: New sequences observed using the plus and numeric approaches to analyzing the selected interaction log datasets.

| Interaction Log Data Terminal Symbol | Approach | Amar et al. | Brehmer & Munzner | Gotz & Zhou | Yi et al. |
|-------------------------------------|----------|-------------|-------------------|------------|----------|
| Battle & Heer                        | Plus     | -           | -                 | -          | -        |
| Liu & Heer                           | Numeric  | -           | -                 | -          | -        |
| Wall                                 | Plus     | -           | -                 | -          | -        |
|                                       | Numeric  | -           | -                 | -          | -        |

We believe these mixed results stem from the tension between optimizing for specificity, ensuring specific user activities are represented, and generality, or designing terminals that can be applied to many tools, when designing taxonomies. On the one hand, our findings demonstrate the utility of theoretical taxonomies beyond their intended use as descriptive tools for designers. Our grammar-based approach reveals how taxonomies can be useful tools for analyzing interaction logs from a variety of systems. On the other hand, our approach demonstrates the limitations of taxonomies. For example, our results suggest that skewed taxonomies may be too general, sacrifice context, and as a result lead to mappings that may not be meaningful for interaction log analysis. In some cases, these taxonomies produced a single terminal for most (e.g., over 95% of) log records, resulting in homogeneous mappings. However, striving purely for specificity may also produce taxonomies with limited applicability, e.g., taxonomies that apply only to one tool. Our research highlights a potential need for more taxonomies that strike a balance between specificity and generality. It also suggests a potential direction for achieving this balance: augmenting taxonomies to include critical contextual cues as input to the underlying regular grammar; for example, details about the system wherein the interactions are being performed.

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### Implications for Log Data Analysis

An important concern when applying taxonomies to interaction logs is the loss of information in the resulting mappings. Taxonomies are designed to concisely communicate the semantics of user interactions. However, a user’s interaction intent is also influenced by the design of the underlying interface, which is intentionally abstracted away from most taxonomies. As an example, consider the filter terminal from the Brehmer and Munzner taxonomy. While mapping the Battle and Heer interaction log dataset, we notice that eight of its distinct log records were mapped to the filter terminal, as shown in Figure 5. After investigating the underlying system details, we posit that these eight filters actually represent three types of filtering interactions, shown in Figure 5: filter the data, filter the visualization, and “other” filter operations. These findings point to a need to augment taxonomies to include system level details to prevent losing user context.

To facilitate the development of new taxonomies, we also need to ensure that log data collection processes scale. Although many interaction logs are shared online, this is no guarantee that others will actually be able to use them. It is critical to create a community-wide process for sharing datasets that will be reusable [BAB+18]. Logs are often collected in an ad-hoc manner that is unique to the system being evaluated, making it difficult to translate these logs to a broad range of analysis contexts [PW18, CGL20]. Generalizeable logging formats must be adopted to make future log datasets applicable to a wider range of analysis scenarios.

### 7 Conclusion

This paper presents a framework that bridges the gap between theoretical visualization task taxonomies and empirical analysis of interaction log data. To do this, we exploit structural parallels between how people express themselves through interactions and language by reformulating existing theories as regular grammars. We represent interactions as terminals within a regular grammar and patterns of interactions as regular expressions over these terminals to capture common language patterns. Regular grammars provide opportunities to express new taxonomies in exciting ways. For example, this formulation can enable future work to express new taxonomies as a mix of low-level and high-level attributes of the inherently hierarchical structure of visual analysis and human reasoning. Our contributions can help the community to create taxonomies that match a broader range of granularities in user intents and strike a subtler balance between capturing the coverage and diversity of interaction log events.

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Figure 5: Eight Tableau log records mapped to the same terminal in the Brehmer and Munzner taxonomy (filter), which could be represented as three terminals: filter, data-point filter, and visualization filter.
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