User-Driven Support for Rapid Visualization Programming in D3

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Fig. 1: Given a recommended code snippet, e.g., a template for “Hover” interactions in D3, the Mirny system supports automatic code augmentation, where the user’s D3 code is mapped to an Abstract Syntax Tree (AST) that Mirny uses to populate and insert the code snippet. In (A), Mirny detects the “fill” variable in the user’s current code (highlighted in orange). In (B), Mirny uses the “fill” variable to automatically populate the “Hover” template (highlighted in green). Finally in (C), Mirny inserts the populated “Hover” template into the user’s code at a detected anchor point in the AST (marked with a star).

Abstract—Visualization templates have emerged as an effective approach to simplifying visualization programming for complex libraries like D3. However, these templates are often treated as rigid artifacts that respond poorly to changes made outside of the template’s established parameters, limiting user creativity. Addressing this challenge requires a more dynamic approach, where tools can respond gracefully to users’ edits when they modify templates in unexpected ways. In this paper, we leverage the structural similarities revealed by templates to design resilient support features for programming D3 visualizations: recommendations to suggest complementary interactions for a users’ D3 program; and code augmentation to implement recommended interactions with a single click, even when users deviate from pre-defined templates. We demonstrate the utility of these features in Mirny, an interactive development environment for D3. In a user study with 20 D3 users, we find that these automated features enable participants to program interactive visualizations with significantly less time and effort. We also characterize key modification strategies used by participants to customize D3 templates. Informed by our findings and participants’ feedback, we discuss key implications on the use of templates for visualization programming.

Index Terms—Human-centered computing, Visualization, Visualization systems and tools, Visualization toolkit

1 INTRODUCTION

Visualization specification languages provide the necessary building blocks for creating interactive visualizations [1], of which D3 [2] is one of the most influential and expressive [2], [3], [4], [5], [6]. However, D3 is a complex library requiring extensive knowledge of web programming and visualization design to use [1], [7], and many D3 users struggle to translate their creative ideas into runnable code and ultimately interactive visualizations [8]. Some visualization tools circumvent this complexity through higher-level code abstractions (e.g., Vega-Lite [9] and Plotly [10]) or direct manipulation interfaces (e.g., Data Illustrator [11] and Lyra [12]). However, by abstracting or eliminating specifications, these tools also sacrifice expressiveness, user control, and creativity [1], [13], [14]. This points to a core question that drives our work: how can we provide the convenience and ease of less expressive tools while still preserving the flexibility and expressive power of D3?

One solution is to abstract popular visualization examples into general-purpose templates [5], [15], and generate programming recommendations based on these pre-defined structures (e.g., Falx [16]). In prior work, templates are often treated as static structures, where users can only modify fixed design parameters to create visualizations. Moreover, these parameters are chosen by the tool developers, not their users. However, users may be interested in changing multiple parts of a template such as aesthetics (e.g., color schemes), data encodings, and mark types. In addition, D3 users often dissect existing examples to extract new functionality they want to build on [8]. For example, users could start working with a bar chart example but eventually transform...
it into a completely different visualization. By limiting how users can modify a template, we hamper these creative activities.

In this paper, we propose a dynamic approach to template-based design. Rather than relying on knowing exactly which template a user is working on, our goal is to identify the structural patterns represented by templates in the user’s code and design automated features to respond accordingly. These features must be resilient, meaning they should work regardless of whether the user is populating templated code or writing code from scratch. To achieve this, we leverage a suite of D3 templates derived in our prior work to build two automated support features for D3: (1) a user-driven recommendation model that suggests suitable interaction(s) to add to a user’s visualization code and (2) a code augmentation feature that can integrate code snippets directly into live user code. To demonstrate the utility of these features, we implemented them in Mirny, an interactive development environment for rapid programming of interactive visualizations in D3 (shown in Figure 2).

We evaluated these features through a study with 20 D3 users prototyping visualizations in Mirny. We find that Mirny enabled participants to implement interactive visualizations in less time and with fewer iterations compared to their typical D3 implementation workflows. We observed participants modifying templates in a variety of interesting ways, which we synthesize into three high level modification strategies: changing the visual styles (e.g. mark colors or mark types), introducing data transformations (e.g., to aggregate or sort data), and removing or adding new data encodings. We also observed unanticipated uses of templates afforded by Mirny, such as participants using templates to initially explore the underlying dataset, then switching to different templates to complete their final designs. Using these findings, we suggest research opportunities to further enhance template-based approaches within visualization tools. All our data and code is shared on OSF.

2 RELATED WORK
Our work draws from research in visualization authoring, recommendation tools, interactive visualizations, template and code generation. We review the relevant literature for each topic below.

2.1 Visualization Authoring Tools
There is a plethora of visualization authoring tools available to users such as specification based toolkits (e.g. [2, 9, 10, 18]), automated tools (e.g. [12, 13, 19], PowerBI), or graphic driven tools that rely on GUI widgets (e.g. [11]). Specification languages are expressive, but require considerable programming skills to use [20, 21, 22]. On the other hand, graphic-driven tools eliminate the need for programming. However, by eliminating the need for specifications, they take away the control from the user [14] and still have a learning curve [7]. Moreover, for visualization users who want to use specification based authoring tools, graphic-driven tools may not be of much help. Our approach aims to overcome this limitation by focusing on how to simplify the implementation process for specification languages instead of completely abstracting the process from users.

2.2 Recommendation Tools
Visualization recommendation systems suggest tasks or visualizations to help users achieve their design goals [23, 24, 25]. These systems can be rule-based, model-based, or both [26]. Rule-based systems rely on established encoding guidelines [27, 28].

Model-based systems use a mixture of expert guidelines, visualization data, and machine learning techniques to generate recommendations [21, 22, 30, 31, 32]. These models are typically trained on data that captures the needs and interest of the target users at the time of collection. As a result, most model based recommendation systems may struggle to respond to shifts in user intent or user interest over time [20, 33]. A popular approach to model prediction problems includes the use of Markov decision problems (MDPs) [34] to account for the long term effects and value of user actions when selecting recommendations for users [35]. Existing modelling techniques could incorporate this form of reinforcement learning to allow for further customization and support within recommendations [35, 36, 37].

We model our recommendations using an MDP.

2.3 Interactive Visualizations
Interactions are critical for helping users gain a deeper understanding of a dataset through manipulation [38, 39, 40]. However, recommendation systems generally focus on variation in visualization design and only provide default interactions such as tooltips and clicks [23, 25]. Interaction+ [41] addresses this challenge by extracting information about visual objects from web pages, and using this information to provide a variety of interactions for manipulating the existing visualization. However, the interaction implementation process in Interaction+ is still abstracted from users. Lyra 2 allows users to specify interactions through demonstration [13], but hides the underlying specification.

We aim to help users incorporate interactions directly into new specifications by giving users access to the actual code. To do this, we need to model the space of possible interaction designs, which is often represented through interaction task taxonomies; we defer to existing surveys for more details, e.g., [42, 43]. We use tasks from Brehmer and Munzner’s typology [43] to model the space of interactions a user may choose to implement in Mirny.

2.4 Templates and Code Generation
Code reuse through templates has been advocated for [44, 45] and leveraged to enable semantic based code search and code completion [46]. Work such as Reiss’s code search approach [46] has informed the development of tools for finding relevant code snippets (e.g., [47, 48, 49]) and recommending significant code templates to complete a users code (e.g., [50, 51, 52]).

Within the visualization community, certain tools use templates to generate visualization designs [13, 53, 54] and styles [5]. McNutt et al. use parameterized declarative templates as a means of abstracting declarative visualization grammars to promote reuse, exploration and simplification of the visualization programming process [15]. Templates have also been combined with code synthesis algorithms in tools like Wrex [55], Falk [16], and Mage [56] to provide readable code in response to users’ interactions with GUI widgets. Lyra 2 [13] focuses on using direct manipulation to make static charts interactive without exposing the underlying code to users.

Current work focuses on templates as static artifacts that users have limited control over. We introduce a dynamic approach, where we identify structural patterns, search user code for these patterns, and propose automated techniques to recommend code templates and integrate them directly into the user’s existing code structure.

3 MOTIVATING USAGE SCENARIO FOR MIRNY
Sandra is a student who wants to create some interesting visualizations for the final project in her data science course. Although

[1] https://osf.io/97mru/?view_only=f259e07ca33441128d5f5dce1fd862c369
who has used D3 in several projects may find it tedious to edit an visualization, preferably with a simple dataset to start, such as to explore how different visualization and interaction types are iteratively implement interactive visualizations. Mirny eases the visualization for her personal records. exports the code from the editor as a JS file and saves a SVG of the visualization. Once Sandra completes her visualization, she recommendation panel so she can zoom into tightly packed sections other; Sandra adds a zoom interaction from the interactions on the is triggered. Some of the data points are really close to each additional information about a data point when a hover event of its behavior in the Editor (Figure 2E). The new code displays code, highlighting the new code block and providing a summary automatically generates the D3 code for a Scatterplot from the data a Scatterplot from Mirny’s Template Panel (Figure 2A). Mirny Sandra clicks on the first recommendation which is a hover interaction from the recommendation panel and Mirny automat-ically extends her current D3 program with the corresponding visualization types (Bar charts, Geomaps, Line charts, Scatterplots, and Force Directed Graphs) as seen in Figure 3a. This suggests that a small subset of visualizations cover the vast majority of D3 users’ needs.

Using Mirny, a new D3 user like Sandra can quickly and iteratively implement interactive visualizations. Mirny eases the cumbersome process of writing D3 code, enabling such users to explore how different visualization and interaction types are programmed in D3 using a single interactive interface. Although this example focuses on a new D3 user (Sandra), it can also easily apply to a more advanced user. For example, a professional analyst who has used D3 in several projects may find it tedious to edit an old example from a previous project, and may still prefer to fill in one of Mirny’s templates instead. We discuss the experiences of both new and more advanced D3 users in section 10.

4 Preliminary Study: Lessons from Analyzing D3 Examples Online

The goal of our work is to streamline the process of implementing D3 visualizations. However to do this, we first have to understand what kinds of visualizations D3 users create and how these users implement these visualizations in D3. In our previous work [17], we qualitatively analyzed 2500 D3 examples shared on GitHub [58], Bl.ocks.org [59] and Observable [60]. Through this analysis, we investigated common implementation patterns D3 users adopt when creating interactive visualizations In this section, we summarize the key results from our analysis and describe design considerations for the Mirny system.

Takeaway 1: A Small Subset of Visualizations are Commonly Implemented in D3. To better understand which visualizations tend to be implemented in D3, we counted the incidence of visualization types across our corpus using Battle et.al.’s D3 visualization taxonomy [3]. We observe that 80% of the D3 visualizations shared online can be accounted for by only five visualization types (Bar charts, Geomaps, Line charts, Scatterplots, and Force Directed Graphs) as seen in Figure 3a. This suggests that a small subset of visualizations cover the vast majority of D3 users’ needs.

Takeaway 2: D3 Implementation Patterns are Consistent Within Visualization Types. In a subsequent round of analysis, we divided our corpus by visualization type, and analyzed the code for similarities and differences across examples, such as differences in the rendering strategy or differences in which interactions were implemented. We found that in most cases, the underlying structure of the D3 code examples did not vary. In other words, the underlying structure and API calls remained the same for each
visualizations in our analysis. As a result, there is a lot of overlap in the implementation code used for visualizations of the same type, with slight variations made to suit a user’s design preferences. We also found that many examples contain links to reference repositories where multiple lines of code were copied from, corroborating the prominence of code reuse in the D3 community. Hence, we curated templates for 8 popular visualizations in our corpus.

**Takeaway 3: Interactions are Commonly Implemented in D3 and Vary by Visualization Type.** We classified interactions implemented in visualizations using Brehmer and Munzer’s multi-level typology of visualization tasks [45]. We observed 6 common interaction widget types: Brush, Click, Drag, Hover, Visualize, and Zoom. 52% of the examples we classified contained at least one or more combinations of interaction widgets (e.g., Hover, Click, Zoom). We find that interactions involving selection of data points such as Hover appear to be universally used in 62% of interactive examples (see Figure 3b). Secondly, some interactions seem to be coupled with specific visualization types, e.g., we observe that graphs are often implemented with the drag interaction. Finally, the number of interactions varied across visualization types. For instance, graphs tend to have at least one interaction whereas visualizations like Line charts had a higher number of examples with no interactions implemented. This suggests that for certain visualization types, users may benefit from having access to multiple interaction types.

### 4.1 Design Considerations

Based on our analysis observations and our personal experiences using D3, we provide three design considerations for our work.

**C1: Support code integration.** Our results corroborate prior work [6], [8] which identify code reuse as a prominent implementation strategy employed by D3 users. In our past work, we developed templates for common data visualizations that D3 users implement. However, these templates on their own are not enough as users may have to introduce new code to implement desired functionality. In such situations, templates are of little use without easy ways of integrating them into new (or already existing) code bases. To support such code transformations, we need to support the automatic integration of template[s] into already existing code. This way a user can create a visualization and also introduce relevant interaction functionality with a simple click.

**C2: Use numbers to drive adaptive recommendations.** Our analysis revealed a wide spread use of interactions to allow users to deeply explore the underlying data. However, we observed that there are many implementation conventions for different possible combinations of visualizations and interactions. D3 users who want to use interactions would have to navigate the space of numerous implementation examples to identify the relevant and compatible implementations. To save users the time and effort, we can provide them with automated recommendations for appropriate interactions for a given visualization type. In this way, D3 users can focus more on implementing the program at hand, rather than having to scour the internet for relevant D3 examples.

User’s preferences are also neither unique nor static, users tend to be interested in things other people have tried when seeking out new interests [20], [33], [61]. Recommendation engines can rely on the large number of D3 examples available on the web to enable recommendations of designs or ideas people may be interested in implementing. We demonstrate this strategy by designing a recommendation model that actively learns from the behaviour of its users to recommend potential interactions a user can implement based on a user’s current visualization design.

**C3: Prioritize familiar interfaces/workflows.** Past research highlights a need for tools to be integrated into users’ workflows. [8], [55] and familiar interfaces [62]. Furthermore, compatibility with other development platforms was one of the design goals of D3 [2]. As such, we prioritize compatibility with users’ workflows and interfaces. We lean on the live programming interface implemented in similar D3 editing interfaces [60] to enable users actively monitor updates to their visualization and quickly catch bugs that may be introduced as they write code (see Figure 2).

### 5 Mirny System Overview

We implement two automated features in Mirny (recommendations and code augmentation) to facilitate visualization programming in D3. In this section, we describe Mirny’s architecture (see Figure 4).

The Mirny web interface provides a user with an interactive graphical user interface through which they can interact with the Mirny system. The web interface consists of four core views: Templates Panel (Figure 2A), Editor (Figure 2B), Visualization Panel (Figure 2C) and the Recommendation Panel (Figure 2D). Mirny supports templates for the 8 most popular visualization types identified in our prior work [17] (Bar charts, Line charts, Scatterplots, Geographic Maps, Force Directed Graphs, Pie Charts, Donut charts and Bubble plots) and 6 interaction types (Hover, Click, Brush, Drag, Zoom, and Visualize). Revisiting our example in Section 3 after Sandra uploads her dataset, she selects a
Scatterplot from Mirny’s list of templates, which triggers a request to the Code Fitter, shown in Figure 4. The Code Fitter loads the corresponding template and fits it to Sandra’s dataset (see section 6). Sandra can see the updates to her code in the Editor and the updated visualization rendered in the Visualization Panel (C3).

Mirny also provides recommendations of interactions that a user can implement in the current visualization. When Sandra selects a recommendation, the Prediction Model (see section 7) receives information from the interface about the current visualization state to perform the necessary analysis to make predictions on future interactions to recommend to Sandra (C2). If a recommendation request is made for a visualization outside of the provided templates, the interface uses the visualizations SVG rendering and the Beagle Annotator [3] to make predictions on what visualization the user is implementing. This information is subsequently used by the prediction model to generate new interactions to be recommended to the users (C2). Subsequently, the Code Fitter automatically generates the corresponding code for the selected interaction (C1) which results in an update to the user’s code to integrate the new code for the requested interaction (see section 8).

6 Populating Visualization Templates

Mirny uses generic templates to generate starter code for users. However, to make these templates usable, D3 users would need to manually modify the code to bind their data to the visual encoding in the templates. Mirny bypasses this step by automatically adapting provided templates to the current dataset a user is using. In our motivating example, when Sandra selects a visualization like the Scatterplot, the Mirny’s Code Fitter first parses through the uploaded dataset to find appropriate data attributes and then transforms the generic template to include these data attributes. Resulting in a “fitted” D3 specification Sandra can use.

Selecting Appropriate Attributes. Each visualization and encoding type has constraints for what data types are the most appropriate [28], which Vega and Vega-Lite exploit to propose useful defaults [63]. For instance ordinal or nominal data should only be utilized for categorical mappings. Mirny applies the same approach to identify which attributes are appropriate for the encodings used in each visualization template. Our Code Fitter considers the data type of each attribute in the source dataset to identify if it is a suitable match for the specified visualization. The first match identified (and not currently implemented) is used as input to be mapped in the template (see Figure 5).

Modifying Templates with Attributes. The generic template in Figure 5 has two variables prop1 and prop2 that need to be updated. Once the Code Fitter identifies attributes with matching data types, it updates the template by replacing the placeholder variables with real ones. In our running example, culmenLength and culmenDepth match the data types of prop1 and prop2. Mirny would thus replace d.culmenLength and d.culmenDepth with d.prop1 and d.prop2 with d.culmenLength in the template’s Abstract Syntax Tree (AST), producing a runnable Scatterplot implementation for the palmerpenguins dataset, shown in Figure 5. This new template code is then displayed to the user in the code Editor. Users are able to change these attributes after the code is rendered.

7 Recommending Code Snippets to Make D3 Visualizations Interactive

Given the prevalent combinations of visualization and interaction types observed in our preliminary analysis (see section 4), D3 users are clearly interested in implementing interactive visualizations. However, it may not be obvious to D3 users which interactions would complement a given visualization. Revisiting our motivating example, Sandra may not know which interactions to implement to enhance her Scatterplot, such as Hover, Zoom, or Brush.

One approach to solving this problem is to automatically recommend compatible interactions anchored on the implementation practices of past D3 users (C2), for example, by training machine learning models to predict complementary interactions for a given visualization. However, users’ programming behaviours and design preferences evolve as their interests shift over time [20], [33]. Thus, a one-shot approach to model training risks generating stale results as users advance their visualization projects. To keep up with the evolving nature of user preferences, our recommendations must also adapt to shifts in user behavior over time. Hence, we leverage Markov Decision Process (MDP) [34] to model users’ interaction preferences and recommend complementary interactions to users as they program D3 visualizations. Here, we provide an overview of the prediction models that drive Mirny’s recommendations.

7.1 Predicting Which Interactions to Implement

Modeling Interaction States. To make recommendations, we first need an understanding of the current state of a users visualization code and use that information to predict what interactions to recommend to the user. We define the MDP for our recommendation engine as a set of states $S$, where each state $s \in S$ is a
set of the interactions that have already been implemented in the user’s code \( \{i_1, i_2, \ldots, i_n\} \). Given that the user could pick any number of interactions to implement, we create a separate state for every possible combination of interactions that we observed from Bl.ocks.org. Furthermore, this interaction set often starts out empty as D3 users seem to implement functional visualizations before incorporating interactions. For this reason, we make the empty state the initial state for our model.

For any given state \( s \in S \), our MDP model produces a ranked list of valid interaction recommendations, ordered by how likely they are to be implemented based on observed frequencies of interaction types among our D3 examples (see section 4).

**Adjusting the Model Based on User Feedback.** Given our interaction states, we model potential interaction implementation steps through a set of user actions \( A \), where each action \( a \in A \) represents a user’s reaction to a recommended interaction \( i_r \). The user can react in one of four ways, given the user’s current state \( s \), and the corresponding future state \( s’ \):

- **Accept** the recommendation by clicking on the corresponding button in the Mirny interface (see Figure 2D), thereby moving to state \( s’ \), given by the equation:

\[
P[s, i_r, s’] = \frac{\text{observations}(s’)}{\sum_{s’} \text{observations}(s’)},
\]

where \( \text{observations} \) computes the total observations of \( s’ \) (i.e., the combination of interactions) in our corpus.

- **Export** the visualization code files (see Figure 2E) and exiting Mirny. This is a cue that the user may be satisfied with her visualization and wants to save it for future use, calculated as:

\[
P[s, i_r, \text{export}] = \frac{\text{observations}(\text{export}|s)}{\sum_{s’} \text{observations}(\text{export}|s)}
\]

- **Undo** an added interaction, suggesting the user was dissatisfied with the interaction and wants to remove it:

\[
P[s, i_r, \text{undo}] = \frac{\text{observations}(\text{undo}|s)}{\sum_{s’} \text{observations}(\text{undo}|s)}
\]

- **Ignore** all of Mirny’s recommendations \( I_r \) by not clicking on any of them in the interface, remaining in the same state \( s \):

\[
P[s, I_r, s] = 1 - P[s, i_r, \text{export}] - P[s, i_r, s’] - P[s, i_r, \text{undo}]
\]

Each time the user transitions to a different state, the probability distributions for outgoing transitions from \( s \) will be recalculated to account for this additional information. We normalize all corresponding probabilities to ensure that they sum to one. Note that since the total interactions that a user will implement is relatively small, these distributions can be computed easily.

**Predicting Transitions Between Interaction States.** We model how likely the user is to transition from one state \( s \) to another \( s’ \) as a transition probability between states. This is represented as a transition function \( T \), which computes the probability that an interaction \( i \) recommended in state \( s \) leads to state \( s’ \) in \( S \), or \( T(s|i_r, s) \). Given the user’s current state \( s \in S \), a recommended interaction \( i_r \), and a corresponding future state \( s’ \), we define our transition function probability as follows:

\[
T_r(s, i_r, s’) = P[s, i_r, s’]
\]

Note that an interaction will only be recommended if it has been observed before. However, we derive our states and transition probabilities using our observations from section 4, ensuring that our MDP model covers D3 interactions that users often implement.

When a user does or does not choose one of Mirny’s recommendations, the MDP is rewarded or penalized accordingly with a positive or negative reward \( R \). We assume that the reward \( R \) for a user’s reaction to recommendation \( i_r \) to be: a small positive number if the user accepts \( i_r \), a large positive value if the user exports, a large negative value if the user undos, and 0 if the user ignores \( i_r \). In this way, the MDP can adapt to match users behavior.

### 7.2 MDP Example.

We demonstrate the behavior of the recommendation engine using a simplified example based on our motivating scenario with Sandra from section 3. A simplified MDP model is depicted in Figure 6.

In this example, we assume that there are only two possible interactions that Sandra will want to implement: zoom and hover. With two interactions, there will be four possible states for our model, shown in Figure 6: no interactions implemented (the initial state), zoom has been implemented, hover has been implemented, and all interactions have been implemented (the terminal state).

Assuming Sandra starts in the initial empty state with her Scatterplot, we can calculate initial transition probabilities, where four (fictitious) transition probabilities are provided in Figure 6.

The intuition behind these probabilities is as follows: Sandra may iterate on her Scatterplot before incorporating any interactions (represented with probability 0.1), and Sandra is much more likely to implement hover than zoom interactions (probabilities 0.6 and 0.1, respectively). There is also a possibility that Sandra could implement a hover interaction but then change her mind and click on the undo button (represented with probability 0.2). For the empty state, our model provides a ranked list with two items, where the first item is hover, and the second item is zoom.

In our motivating example, Sandra clicks on the first recommendation of hover, representing the accept reaction. In this case, the MDP model receives a small positive reward for providing a useful recommendation, represented by the blue line in Figure 6.

However, suppose that Sandra undoes her last added interaction, this results in a negative reward to the MDP model, represented by the red line in Figure 6. If Sandra exports her visualization after adding the interaction, the MDP model receives a large positive reward for providing helpful recommendation[s] to Sandra.

### 7.3 Preliminary Model Accuracy Results

To ensure that our recommendations align with our observations from section 4, we performed leave-one-out cross validation [64] of the MDP model using our coded dataset. For each visualization example from our dataset, assuming the initial empty state, we classify a recommendation as correct only if they included the all interactions implemented within that example. Overall, our model has an average accuracy of 76%. For certain visualization types, this accuracy can be improved, e.g., for zooming interactions (60% accuracy). Such cases can be improved in future work by adding more input observations for the model to train on. However, this evaluation does not take into account how users’ reactions to recommendations may improve the model’s predictions over time. We discuss our evaluation with actual D3 users in section 9.

### 7.4 Predicting Visualization types

We described how the recommendation engine supports interaction predictions when the user selects a visualization template first. However, our implementation in the Mirny system can also support recommendations even when the user does not select a template. To do this, Mirny utilizes the Beagle Annotator developed by Battle et al. [3] to enable real-time prediction of the visualization a user is currently implementing. With this annotator, Mirny can predict if a user is implementing a Scatterplot, or some other visualization type by extracting the SVG elements of the visualization and running it through the Beagle Annotator’s decision tree classifiers.
A major goal of this work is to reduce the challenge of this may include displaying additional information about the data attributes in the user’s code by parsing through its AST. Using mark properties, need to be incorporated into the hover template. For the circle marks, and the data attributes passed as inputs to the marks in Sandra’s Scatterplot, then the code that sets properties interaction needs to update certain properties of selected circle marks. Considering our running example from section 3, if the hover event it is initially unclear which variables in the user’s code file map from interaction templates, specific inputs from the user’s code changing it’s position on a drag event. To create meaningful code to the state of the selected mark (or non-selected marks) such as selected data point through a tooltip or making modifications to the state using a Markov decision process (or MDP) model. Here is a simplified example of how the Mirny MDP model is structured with two interactions (zoom and hover), explained in subsection 7.2.

### 8 Augmenting User Code

Recommending relevant interactions could help D3 users find interesting interactions for their designs. However, these recommendations alone would not be very useful to visualization designers. Users would still have to search for example implementations and figure out how to integrate the code for these interactions into their work. A major goal of this work is to reduce the challenge of integrating code from different sources into a user’s visualization specification. We envision a user clicking just a single button to automatically add an interaction to her design (C1).

Given a recommended interaction selected by the user, we need to be able to modify the existing user code to include the corresponding code for this interaction. The D3 API supports six interactions (i.e. Hover, Click, Brush, Drag, Visualize and Zoom) which have been identified and analyzed in section 4. The underlying code base for these interactions have been manually extracted into pre-generated templates that Mirny uses to automatically generate code for selected interactions.

Once a user selects a recommended interaction, we apply a series of code rewriting steps to merge the template into the user’s current code file. Specifically, we translate the user’s code file into its corresponding abstract syntax trees (or ASTs), analyze the trees for potential insertion points, and merge the interaction code template with the user’s code file at a selected insertion point. This process happens in four steps which we describe below.

#### Step 1: Identify Input Variables for the Interaction Template.

Interactions often result in changes to the state of the visualization. This may include displaying additional information about the selected data point through a tooltip or making modifications to the state of the selected mark (or non-selected marks) such as changing its position on a drag event. To create meaningful code from interaction templates, specific inputs from the user’s code need to be extracted. However, given the abstract nature of code, it is initially unclear which variables in the user’s code file map to the required inputs within a given interaction code template. Considering our running example from section 3 if the hover interaction needs to update certain properties of selected circle marks in Sandra’s Scatterplot, then the code that sets properties for the circle marks, and the data attributes passed as inputs to the mark properties, need to be incorporated into the hover template.

Hence, the first step of the code augmentation process is to identify analogous variables between the user’s code and the interaction template. Since the properties needed for the interaction templates are known beforehand, we can identify the appropriate data attributes in the user’s code by parsing through it’s AST. Using our motivating example, when Sandra selects the Hover interaction from the recommendation panel, the templates we use assume that at the end of the Hover event, properties like the color and radius of the circle mark would need to be restored to its original value. The Code Fitter parses through Sandra’s code to identify the input variables that are needed to make a viable template, searching within API calls, variable, and function declarations for the needed components. For instance, suppose Sandra’s code creates and sets the fill of the circle marks in a scatter plot using the following code:

```javascript
svg.selectAll('.bubble')
  .data(data)
  .enter().append('circle')
  .attr('r', (d) => radius(d.culmenLength));
  .attr('fill', (d) => color(d.species));
```

The code fitter parses through the AST of her code to find where the circle marks’ fill attribute is assigned and extract the assigned value (or in this case function) (see Figure 1). If an attribute is not found within the code, a default value is assigned.

#### Step 2: Populate the Interaction Template.

Once all the required input variables have been identified, the interaction template is modified to include these input variables. This process is similar to the modifying templates with attributes process explained in section 6. All API calls are updated with the right variable names and parameters as needed. For example, the mouseover event of the hover interaction will be populated with the original function to determine the circle’s fill as seen in Figure 1.

| Generic Template | Populated Template |
|------------------|-------------------|
| .on('mouseover', (d) => { d3.select(this) .style("fill", "prop1"); }) | .on('mouseover', (d) => { d3.select(this) .style("fill", (d) => color(d.species)); }) |

#### Step 3: Identify Anchor Points in the Users’ code for Insertion.

In D3, the specification of interactions is imperative [63], hence, the interaction code cannot be placed just anywhere within an existing D3 specification. Before modifying the user’s code file, we must first identify the appropriate locations within the code to include new interactions. We refer to these locations as anchor points.

Anchor points signify nodes within the AST that need to be changed to support a new interaction. For example, to add the Hover interaction to Sandra’s code, a new node has to be created for the interaction code and added to her code at the point where the visual marks are created. Because we know she is creating a Scatterplot, this would translate to the code block that contains the .append(circle) API call. AST’s are traversed using a depth first approach, hence, identifying the anchor point simply involves iterating over the AST, with the objective of finding the node which has the appropriate data binding API call in it’s child branch. For our hover example, the anchor point would translate to the first node we identify that has the .append(circle) expression as a member of it’s child nodes as seen in Figure 1.

Anchor points for most visualizations generally can be found where the data binding to visual marks occurs. However, for complex interactions such as Zoom or Brush interactions helper functions and new visual elements need to be added to the user’s code, as such multiple anchor points are needed. Helper functions need to be accessed from anywhere in the D3 script (i.e. have a global scope), hence their anchor point is by default the body of the entire script. Elements, such as rects, to enable zooming or
brushing over sections of the visualization need to be added over the entire SVG, as such they use the node that binds the <SVG> element to the webpage, as their anchor point.

**Step 4: Insert the Populated Template into the User’s Code.**

Once a template has been populated and the anchor point has been found, the template code is then added as a new node in the user code at the selected anchor point. As a result, the populated template code becomes a new sub-tree within the AST of the user’s code. The template’s root node can either be appended or prepended to and in some cases replace the anchor point.

The nature of the template node and semantic correctness of the code are taken into consideration when determining which of the insertion actions to perform. Code that introduces a new code block after the anchor point typically will use an append operation, whereas new code that goes before the anchor point will use a prepended operation. For instance, adding new code that defines a tooltip for the Hover interaction will be included before we call any hover event. As such, the code for the tooltip will be added before the anchor point using a prepended operation. The replace operation is usually used when adding new code as part of an already existing code sequence in the users code. This is due to the fact that ASTs are traditionally traversed depth-first, so the new code will have to become a parent node to the anchor point. In our motivating example for the Hover interaction, the code that handles the mouseover and mouseout events will need to be added to the entire anchor point's branch. This will require a replace operation to make the template code’s AST a parent node of the anchor point as seen in [Figure 1]. Finally, Mirny converts the new AST back into code, and updates the Editor to display the updated code file.

```javascript
svg.selectAll('.bubble')
  .data(data)
  .enter().append('circle')
  ... attr('r', (d) => radius(d.culmenLength));
  style('fill', (d) => color(d.species));
  on('mouseover', (d) => {...});
  on('mouseout', (d) => {...});
```

### 9 Evaluation: User Study Design

In previous sections, we introduced two automated features with the aim of reducing the burden of visualization implementation for D3. We implemented these features in an interactive development environment called Mirny. In this section we focus on evaluating if these automated features lead to measurable improvements in how D3 users implement interactive visualizations. Our study was preregistered on aspredicted.org.

**Participants.** We recruited 20 participants from mailing lists and social networking sites (4 female, 15 male, 1 non-binary) between the ages of 18 to 44. To ensure that all participants had sufficient understanding of D3 to complete the study tasks under time constraints, we required participants to have at least 3 months of experience working with D3.js. 11 participants had 3 months to 1 years experience, 3 had 2 - 3 years experience, 4 had 4 - 5 years experience and 2 had 5+ years of experience. Participants self-reported to be proficient in creating visualizations. Each session took approximately 1 hour and 30 minutes and participants were compensated with a $20 Amazon gift card.

**Tasks.** To observe how participants use these automated features in various visualization implementation contexts, participants were asked to perform two tasks for the study. Participants were allowed to implement whatever visualization or interaction type they chose as long as they met the requirements for each task.

- **Task One: Targeted visualization design:** For this task, participants were asked to use the Cherry Blossoms dataset to create a visualization meeting specific design requirements. The output visualization[s] had to meet two requirements: target users of the output visualization should be able to (a) identify correlations between two specific variables, and (b) interact with the data points in the visualization.
- **Task Two: Exploratory visualization design:** Participants were asked to choose between the popular Car4 and Iris datasets, and then brainstorm what type of visualization they would like to implement. Then, participants were asked to implement this visualization and include at least one interaction in their visualization.

**Experiment Conditions.** Participants experienced two different Mirny setups across our tasks, resulting in four total experiment conditions (2 tasks × 2 interface setups). In one setup (baseline), participants only had access to Mirny’s visualization templates, but not Mirny’s interaction recommendations. In the second setup, participants had access to all of Mirny’s features. Condition order was counterbalanced across the visualization tasks. We tuned our experiment conditions through a pilot study, described below.

**Pilot.** We conducted a pilot study to fine tune our initial protocol. One important parameter we sought to tune was task difficulty, i.e., should participants be asked to implement D3 visualizations from scratch as a task condition (the common case), or should participants be provided with Mirny's templates? In the pilot study, all participants (2 female, 1 male) were familiarized with Mirny and were asked to perform the tasks described above. For task one, we provided access to Mirny’s visualization templates for two of the three pilot participants, while one participant implemented visualizations from scratch. Participants were able to use both the predefined templates and recommendation panel for task 2.

We observed that the participants who were provided with templates only used Mirny’s templates while the third participant copied code from a D3 example they found online. The participant who had to write their D3 code from scratch spent 45 minutes implementing a single visualization and was unable to implement any interactions, thus unable to complete the task. The participants who were provided with templates took less than 15 minutes to create a single interactive visualization for the same task. These results show that it would have been difficult to conduct a one-hour experiment if participants had to create visualizations from scratch, and the experiment time could be drastically reduced if templates were always provided. Hence, we decided to provide templates for all tasks and experiment conditions. However users could always opt to write their own code from scratch if desired.

**Protocol.** Participants were required to complete a demographic survey to determine eligibility for the study. Each session started with a Pre-study session where participants were familiarized with the study, and signed the consent form. They then proceeded to a training session where the experimenter walked them through the interface functionality via a prerecorded demo of the interface. Participants were then given 5 minutes to explore the full Mirny interface themselves and ask any question they had about the interface. Once participants were comfortable with the interface, they proceeded to complete our two study tasks. The experimenter limited guidance to only situations where the user reached a

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3. Pre-Registration available at [https://aspredicted.org/blind.php?x=cc46nd](https://aspredicted.org/blind.php?x=cc46nd)
4. [https://www.kaggle.com/abineshkumark/carsdata](https://www.kaggle.com/abineshkumark/carsdata)
Fig. 7: Results from analysis of data collected during evaluation of Mirny. T = Templates only, TR = Templates + Recommendations.

complete standstill and was unable to figure out the next step. Participants were allowed to use any external resource they wanted such as Stack Overflow or Bl.ocks.org. No time limits were placed for any of the tasks. Once all the tasks were completed, the participants completed a short exit survey and interview.

Data Collection For each session, an experimenter observed the participants while they performed their tasks and took notes. Logs of participants’ interactions with Mirny were also recorded through the Mirny back-end, which captured all click and keyboard events. We collected data from the post-task survey on participants’ ratings of Mirny’s features to capture participant feedback. Finally, video and audio were recorded to capture participants’ interactions with the interface and responses to the exit interview questions.

10 Evaluation: Analysis & Results Here we present three analyses of our study data: measuring session durations and design iterations (subsection 10.1), classifying template usage and modification (subsection 10.2), and summarizing participant feedback (subsection 10.2). We have four hypotheses we tested across all three analyses:

- **H1**: Users produce a higher number of executable visualizations when provided with visualization templates compared to when users program visualizations from scratch.
- **H2**: Users produce a higher number of interactive visualizations provided with visualization templates and interaction recommendations, versus only visualization templates.
- **H3**: Users spend less time implementing interactive visualizations when provided with visualization templates and interaction recommendations, compared to when users only have access to visualization templates.
- **H4**: Users find D3 more interesting and more useful when provided with both visualization templates and interaction recommendations, versus only visualization templates.

10.1 Automation Simplifies D3 implementation

To understand how code recommendation and augmentation support the visualization implementation process, we collected data on the number of interactions participants implemented for each visualization (H2) and the time taken to implement a fully interactive visualization, i.e., time taken to render a single visualization + time taken to implement a single interaction (H3). We fit linear mixed effects models with condition and condition order as fixed effects and participant and dataset as random effects. We find a significant effect for interface layout on the number of interactions \( H2: (\chi^2(3, N = 20) = 13.406, p = 0.011) \) and time to implement an interaction \( H3: (\chi^2(1, N = 20) = 3.85, p = 0.0499) \). Recommendations + code augmentation led to 1.9 more interactions implemented per visualization compared to only 0.7 interactions when using only templates. Participants also implemented interactions 3.2x faster when recommendations and code augmentation were provided (5 minutes versus 16 minutes for templates only). Our survey results show that participants found the recommendations to be useful (Median(M)=2/Agree, \( \sigma = 0.6 \)) and instrumental in helping them gain new ideas of interactions to implement (Median(M)=2/Agree, \( \sigma = 0.6 \)). Participants also believe automated features streamline the visualization implementation process in D3 (Median(M)=2/Agree, \( \sigma = 0.5 \) see Figure 7c).

10.2 Templates Facilitate Design Iteration To assess the efficacy of Mirny in helping users program visualizations, we formulated two hypotheses that compare Mirny’s templates to users’ typical workflows (H1) and interests in Mirny (H4). However, based on the results of our pilot study we needed to provide templates for all participants, affecting our analysis methods. While we do not quantitatively test H1 and H4, we have informal support for this hypothesis based on our observations of user behaviour and feedback from participants.

Participants default to templates to complete tasks. We expected that some participants would want to write their own code to complete tasks and provided an option to support this. Contrary to our expectations, every participant in the study defaulted to using Mirny’s templates, regardless of D3 expertise.

Template Modification Strategies. Our findings suggest that templates are a great starting point for users but require modifications to fit users’ needs. We observed a total of 33 distinct code modifications to Mirny’s visualization templates (n=22) and interaction templates (n=11). The majority of these modifications involved changes to accommodate stylistic preferences of participants (n=22), such as changes to the fills for marks and their associated color schemes, changes to the displayed layout of visual elements such as text, or changes to add new behavior to interactions. For example, P16 modified the code for a hover interaction to remove the default tooltip and instead change the opacity and size of other circles outside of the species class of the selected data point(s). P16 also modified the code to increase the size of all circles in the selected species class to make them more prominent.

We observed 6 occurrences of participants modifying Mirny’s visualization templates to transform data such as aggregating, sorting or grouping data attributes. For instance P15 modified the bar chart template to aggregate the number of cars produced each year and group them by country of origin. We also observed 5 modifications to introduce new data encodings or visual marks to the templates, which resulted in particularly interesting visualization redesigns. For example, P19 introduced an encoding mapping the LastFrost attribute to circle size in their Scatterplot implementation; more examples can be seen in Figure 8.

Unexpected uses of templates. We observed three unexpected ways that participants used templates while completing the design tasks. First, we find that 12 participants explored multiple templates...
to find visualization design options that would be appropriate for solving the required task. While most participants eventually settled on Scatterplots as their final design, they often explored charts such as line, bar and pie charts before making their selection. We also observe that a subset of these participants (n=4 of 12) used an initial template to perform exploratory data analysis, then chose a different template later on to present the results. For instance when completing task two, P7 used the bar chart template to analyze the distributions of various data attributes. Then, they used the resulting insights to select attributes to present in their final Scatterplot.

### 10.3 Participant Feedback

Participants reacted favorably to the features implemented in the Mirny system. In particular, participants often explained that the templates helped streamline the process because they provided starter code which helped save time finding suitable code. On their own, participants would have to spend hours finding example code. 13 participants report using some sort of template code from the internet (e.g., Observable or bl.ocks.org) while 7 participants cited that they would have written the code from scratch using a text editor. P12 describes creating a personal library of templates, stating, “I have this library of previous stuff that I’ve created. So I usually just take one of those and then start adding to it.”

We observe that having access to the code for both the visualizations and interactions was perceived as useful by participants and helped improve their understanding of the D3 designs. This sentiment was also shared by more experienced participants who explained that access to code may not be useful for them due to their knowledge of D3, but would be useful for people who are just starting to learn D3. For P9 who instructs a visualization class, teaching D3 is a difficult task as students would typically need to learn HTML, CSS, Javascript and D3 all at the same time. A tool like Mirny would be instrumental in helping his students focus on learning the basics of D3 without being burdened with learning all these other languages at once. “I also teach people d3. And I think this would be great...Having something like this, that creates the chart and the code and comments the code, so you can read the code. They [students] would like cry tears of joy to have this.”

Surprisingly, some participants did not understand the value of interactions. For example, when asked if interactions were effective, P17 said “I mean, if you want to add an interaction, this is definitely helpful...But in general, I think I prefer non interactive visualizations”. This finding suggests that our community still has work to do in conveying the importance of interactions to users.

### Limitations

Participants welcomed the features implemented in Mirny, however, our approach is not perfect, and participants made suggestions for further refinement. Participants expressed the need for insight on why certain recommendations are made, e.g., P10 said “instead of having the recommendation shift, just give more insight as to why this is being recommended, basically”. Participants also suggested including more widgets to support further customization of D3 code, e.g., P15 said “...maybe adding something like the components, to support selecting an axis or legend. If those are also given as part of templates to completely customize code, that might be more helpful”. Participants also found the live updates feature of the Mirny system to be a hindrance when debugging their code. Participants suggested adding a run button to allow them update the visualization output when desired.

### 11 Discussion

The results of our evaluation show that the automation features presented in this work streamline the visualization design process, allowing D3 users to quickly explore and iterate over different visualization designs(C1, C3). Recommendations provide users with ideas for interactions (C2) and allow users to integrate code from different interaction templates into their visualizations (C1). Furthermore, we observe a preference for templates as 1) a starting point for their visualization designs and 2) a tool for the exploration of appropriate designs for a specific task.

Templates are often perceived as a baseline that can be used for the creation of visualizations. However, our observation of D3 users shows that templates can also be used as an intermediate step in the design process. Participants in our study often used the provided templates to iterate over ideas by first exploring different visualizations (e.g., line or bar charts) before settling on their preferred design. In this way the provided templates allowed users to reason about their visualization design choices and connect design ideas. Future research on the use of design templates should allow for dialog between users, templates and recommendation engines to improve the visualization programming experience. For instance modularized templates for each part of a visualization (e.g axes, marks) could allow users to mix and match designs. This may also be extended to build systems that could recommend potential visual features users may be interested in.

Our work currently focuses on code integration for interactions. We observed during our user study that users may be interested in changing a template from one visualization form to another. For instance changing a line chart to a connected scatter plot (see Figure 8p). In future work, we hope to explore extending our automated features to support more complex template transformations to change the structure and arrangement of visual marks in response to data transformations. For instance, a bar chart template can be changed to a stacked bar chart when a user aggregates data based on a specified data attribute.

We also observed participants augmenting our templates in three key ways: to (1) accommodate their stylistic preferences, (2) perform data transformations and (3) introduce new encoding[s] to the visualization. In the future, we need to deeply investigate user’s reasoning during the design process. Such studies will help identify the context for how and why a template is modified, and also understand what role datasets and stylistic preferences play in the modification process. Finally, new research may explore how automated visualization authoring tools can account for these modifications as they generate and recommend designs while preserving user agency and individual design preferences.
12 Conclusion
In this paper, we present a new approach to help users harness the expressive power of complex visualization languages like D3. We contribute two automated features to help users program interactive D3 visualizations with less time and effort: (1) a recommendation engine for suggesting complementary interactions to add to a D3 visualization, and (2) automatic code augmentation to incorporate suggested code snippets to live user code, even when users are not following a pre-defined template. We implement these features in Mirny and in a user study with 20 D3 users, we find that they enable users to create interactive visualizations faster and in fewer iterations compared to the typical D3 development workflow (i.e., when automated features are not available). We also observe three key strategies used by D3 users to customize visualization templates and unexpected uses of visualization templates during design. Our work highlights important takeaways on the use of dynamic templates and D3 users perspectives that we hope will influence future work on visualization authoring.

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