Provenance and Annotation for Visual Exploration Systems

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Abstract—Exploring data using visualization systems has been shown to be an extremely powerful technique. However, one of the challenges with such systems is an inability to completely support the knowledge discovery process. More than simply looking at data, users will make a semipermanent record of their visualizations by printing out a hard copy. Subsequently, users will mark and annotate these static representations, either for dissemination purposes or to augment their personal memory of what was witnessed. In this paper, we present a model for recording the history of user explorations in visualization environments, augmented with the capability for users to annotate their explorations. A prototype system is used to demonstrate how this provenance information can be recalled and shared. The prototype system generates interactive visualizations of the provenance data using a spatio-temporal technique. Beyond the technical details of our model and prototype, results from a controlled experiment that explores how different history mechanisms impact problem solving in visualization environments are presented.

Index Terms—Visualization, interaction model, provenance, annotation.

1 Introduction

The goal of visualization is to provide insight to a user. For interactive visualizations, this insight is gained via exploration of the data using a variety of techniques. What is typically presented when results are reported, however, are static images that are intended to provide other people with a similar insight. This disconnect between the original discoverer and the recipients of the information gained from the visualization raises significant questions: What is the context of discovery? What were the sequence of steps used by the researcher to gain the insight? Ultimately, static representations are extremely valuable [59]. However, these static representations only tell a small part of the visualization story—a story made far richer and more valuable by considering the provenance of insights gained through visualization.

This research makes an assumption that the knowledge discovery process is, indeed, a *process*, and that the steps that a user takes to discover knowledge are as important as the knowledge itself. As described by Fayyad et al. [26], the Knowledge Discovery in Databases (KDD) process is frequently depicted in terms of a number of iterative steps, as shown in Fig. 1. There are, of course, obvious similarities between the KDD process and the data visualization pipeline [14], [48], [64] shown in Fig. 2. A critical aspect of the process is the implied interaction with a user. Obviously, the user is involved with problem selection, as well as the interpretation of the results. Often, the user may review the results and develop a more refined problem statement, which initiates another iteration of the process.

The main contribution of this research is a conceptual model of user interaction and annotation for data visualization. The model concisely captures changes to the state of the visualization made by the user in a way that provides recall of the steps that a user took to achieve the visual representation. We describe an implementation of the model applied to 3D molecule visualization. User studies were performed to evaluate the impact of the proposed model on users in the context of knowledge discovery tasks.

Ultimately, we seek to recognize the interactions and annotations as first-class objects. Knowledge of past interactions can be exploited by analysts to recall past visualizations, extend other's work, and draw broad comparisons across data, time, user, and location. This research is a fundamental contribution to developing solutions for an emergent research area: *information provenance*. Problems in knowledge and data provenance [9], [10], [33] are gaining interest, with broad applications to the advancement of scientific discovery [47].

Provenance is a term that refers to the lineage of an item. While some people associate the term with artwork and the lineage of who owned or possessed the piece, we use it in the context of the information discovery process. The model that we are presenting supports provenance by fully documenting the discovery process. The prototype demonstrates how users can interact with the history of interactions and capture annotations in the same context. Conceptually, the model separates the interaction from the data. This allows for the exchange of not only the result of a visualization, but precisely how the result was achieved. Another user may take the interaction data and use it against a different data set to see how general the technique may be.

The remainder of this paper is structured in the following way: In Section 2, we describe work that is related to this research. Following that, we define the interaction model in Section 3. We then present implementation considerations for the model using our prototypes for demonstration purposes in Section 4. A substantial user evaluation is presented in Section 5. Extensions to the model are described in Section 6. Lastly, we conclude in

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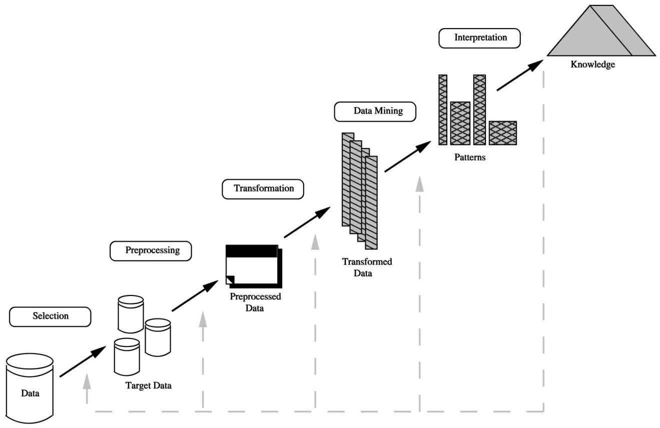

Fig. 1. The KDD process.

Section 7 with a discussion of how the model can be applied and a description of our planned efforts.

2 Related Work

This section contains a summary of the main findings and research issues that are relevant to this project. These are data provenance, annotation, history tracking and sense making, and visualization frameworks.

2.1 Data Provenance

The concept of provenance has emerged in the database community and the grid computing community. In databases, several challenges have been identified, including the complexity of linking data through joins and queries [8], [9], [10]. This is particularly important since data exists in tables but is accessed and updated through queries. More recent work has investigated Post-it-style notes for relational databases [5], [17], [57]. Within grid computing, issues surrounding provenance and annotation are particularly important. One focus is on the source data files, which are annotated with information describing when and where the files were generated. A different focus is on descriptive workflow languages [32] that specify how files are processed, which programs are executed, etc.

2.2 Annotation and Collaboration

Sticky Notes [12], and StickyChats [18] are two systems that use a sticky notes metaphor to give annotations context. Sticky Notes is a system developed specifically for protein visualization. StickyChats allows user to insert text annotations into electronic documents and supports asynchronous collaborative annotation. A model of annotation based on layers introduces multivalent annotations [49].

The Iris Annotator [28], AVS [60], and the IBM Data Explorer are Modular Visualization Environments that support scientific visualization and collaboration but not remotely. The JETS system [54] supports multiple types of annotations and multiple types of data and can be employed on different platforms, but restricts interaction to one user at a time. HABANERO [15] supports multiuser collaboration but is restricted to synchronous viewing.

The COVISA system [7], [63] was developed to understand group work requirements in visualization. One attribute of COVISA is tapping off data at the point where it moves from one module to another and sharing it between collaborators. The Visualization Workbench [34] is a system that supports multiple users manipulating complex visualizations through lightweight clients.

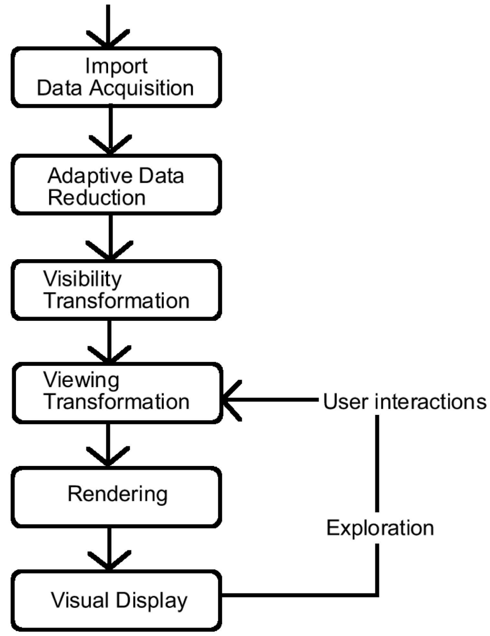

Fig. 2. The visualization pipeline.

Digital ink-based annotation systems have more recently been developed [3], [20], [25]. Some annotation systems focus on documents as the underlying information [18], [43], [53], while others focus on scientific data [31] or video data [52], [1]. Annotation has been closely linked with collaboration technologies [19], [45].

2.3 History Tracking and Sense Making

Perhaps the original provenance system is the Memex, which linked together all of the information sources that a person accessed or would need to access [11]. The concept of a cognitive trace associated with visual representations describes the cognitive aspects of interaction histories [55]. Specifically for visualization systems, history tracking has been implemented for parameter setting [21], [41], [51]. Approaches that focus on data-to-visualization mapping [40] are influenced by the data-flow nature of the visualization pipeline [64].

A graph-based model, similar to the one we have proposed, captures view transformations [37]. Histories for Web searching focus on Web navigation [38], [46], [61], [62]. History tracking for complex user interfaces are primarily focused on undo and redo capabilities [4], [22], [27], [29], [39]. The TaskTracer system [24] keeps track of activities across applications and files.

Our project addresses problems in sense making [42], [50], which seeks to synthesize multiple sources of information. Because the goal of visualization is to provide insight to the user, this project extends the capabilities by allowing them to share their insights in fundamentally new and interesting ways.

2.4 Visualization Frameworks

Our research is focused on knowledge discovery that involves visualization, even though the model may extend to support other exploratory paradigms. Because of the focus on visualization, a number of prior related works are relevant. A general discussion of the process of mapping is provided by Card et al. [14]. Early discussions characterize the mappings from the data to the appropriate visual representation [13], [56]. More recently, the snap-together paradigm was demonstrated to take advantage of relational schema-to-visualization mapping [48]. Mappings based on data types are also investigated [58]. The data-space model by Chi is a key starting point for this project [16]. In particular, the characterization of the process as being state-based, with specific user-driven transformations affecting transitions between states, is an ideal framework on which to base history and provenance tracking systems for knowledge discovery.

3 The Model

We have approached the development of our model from two different perspectives. First, from a pure tracking standpoint, the model must accurately capture the user's interactions. We will refer to a model that tracks the user's exploration as an "Interaction Model." The second perspective considers the observations that a user may make while exploring the visualization. In this extension to the model, users add annotative information to the visualization, thereby expanding the information base—a natural part of the scientific discovery process. This framework for annotation is described in the next section.

The model is not designed for any one specific visualization domain. However, in order to illustrate the model, we use molecular visualization of a crystal structure as an example.

3.1 The Interaction Model

We base the model on directed graphs, with nodes signifying measurable states of the visualization system and edges denoting transitions between the states. The states of the system are generically captured in the model, leaving it up to the implementation to define the specific contents of the state and transition information. For example, as described in [37], the transitions might contain discrete interactions, such as zoom, rotate, translate, or other interactions as described in [16].

Let $I = I_1, \ldots, I_j$ be a set of interaction descriptions, for example, $I = \{\mathrm{ZOOM}, \mathrm{ROTATE}, \mathrm{TRANSLATE}, \ldots\}$. Let $S = \{S_1, \ldots, S_m\}$ be the set of states generated during a user's exploration of a visualization. Each state is defined as the pair $(StateID, StateInfo)$, with $StateInfo$ signifying a descriptive or syntactic definition of the state, depending on the implementation. Let $T = \{T_1, \ldots, T_n\}$ be the set of transitions. Each T_i is a triple $(FromID, I_j, ToID)$, with the interpretation: Starting from state S_i with $StateID = FromID$, the user performed interaction I_j, which resulted in a new state S_k with $StateID = ToID$. The formal definition of the interaction model is a triple $M = (S, T, I)$. As shown in Fig. 3, the graph structure is shown for a couple of visualization states.

The model does not restrict multiple modes of interaction. For example, multiple stimuli (e.g., voice command and mouse motion) can be captured via two transition edges between states, with the interpretation being parallel interaction. System-generated transitions can be supported in a similar fashion, either by multiple sensors or by simulation programs. The encoding of the interactions is system-specific.

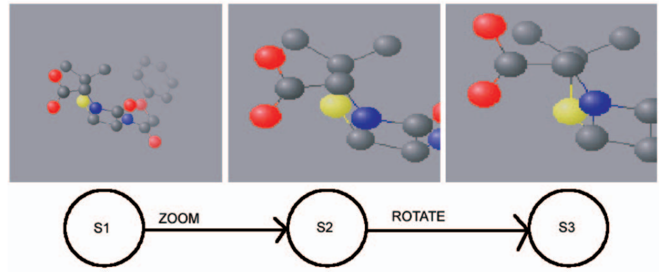

Fig. 3. An example instance of an interaction model. In this exploration, the user zoomed and then rotated the data.

3.2 Annotation Framework

Extensions to the basic interaction model are necessary to support annotations. Although, in this paper, we focus on user-generated annotations, the model does not preclude incorporating system-generated annotations, as is done in bioinformatics, for example, with gene annotation systems.

By generalizing the interaction graph structure, the model can support annotations of system states, annotation interactions, or even annotations of annotations, which might be used by collaborators to track collaborative discovery. We add a type attribute to both edges and nodes. The type attribute is taken from a set of types that may vary based on particular implementations. The model does not presuppose any interpretation of the types. More specifically, the definition and interpretation of the types is an implementation detail.

The simplest application of the model is to annotate the states of the visualization system—for example, using a small set of the types for the example model: 1) States of the Visualization, 2) User Interactions, and 3) Annotations. We will use the same interactions (i.e., ZOOM and ROTATE) that were used in the previous section. In this example, we will assume that the user follows the general process of 1) observing the display, 2) making an annotation, and 3) applying an interaction. For this example, the annotation data is represented by text. However, there is no restriction on the mode of input used to perform the annotation. Fig. 4 shows the interaction graph for this example. The contents of the annotation nodes are represented as text.

Like the interaction model, the annotation framework does not restrict the number of annotations for a specific state. For example, Fig. 5 demonstrates both a typed and drawn annotation for the visualization [25].

The interaction model and annotation framework can support a dialogue-like interaction. For example, Fig. 6 shows an interaction graph in which the first annotation is remarked upon by a second annotation. For collaborative applications, we expect this capability to link observations across system states and users to be extremely powerful.

4 Prototype Implementation

In this section, we describe our prototype implementation of the interaction model. The prototype implements interaction tracking and annotations for a 3D molecule viewer.

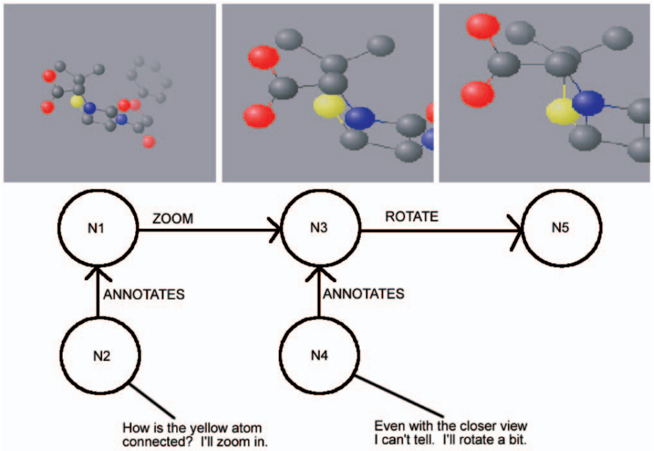

Fig. 4. An example instance of an interaction graph articulated with annotations. The user annotates each state of the visualization and then performs the interaction.

4.1 3D Molecule Visualization

Our prototype implements the pull strategy described in the previous section. We modified a system for visualizing multivariate data to have the CheckState, GetState, and SetState methods as depicted in Fig. 7. The state information that we tracked within the system was a viewpoint model—camera position and direction within a 3D environment. Fig. 7 shows a general design for the system.

The most interesting aspect of our prototype is the model manager interface, which exposes the interaction graph to the user. The resulting application allows the user to interact with the visualization system as well as the interaction graph. Fig. 8 shows a screen capture from the model manager. The user interaction was a simple sequence of zooming operations to display an overview of the entire data set.

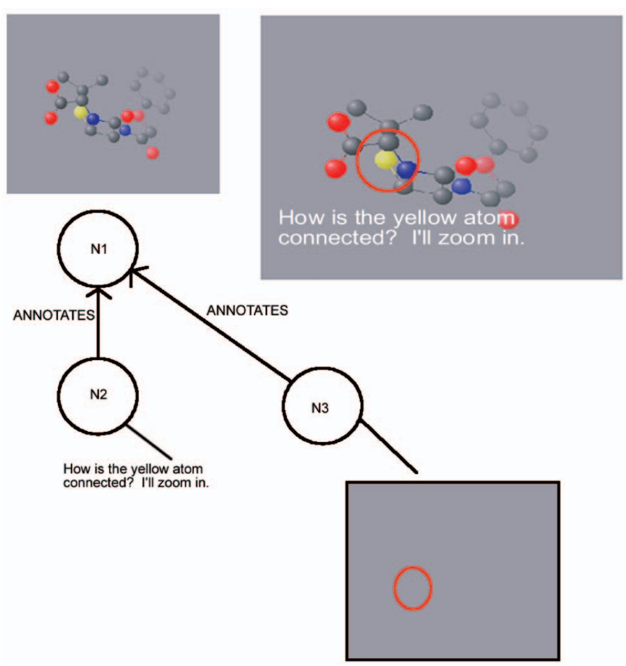

Fig. 5. In this interaction graph, the user has created two annotations for the same state. An example of what might be displayed to the user is shown by combining the annotations with the visualization.

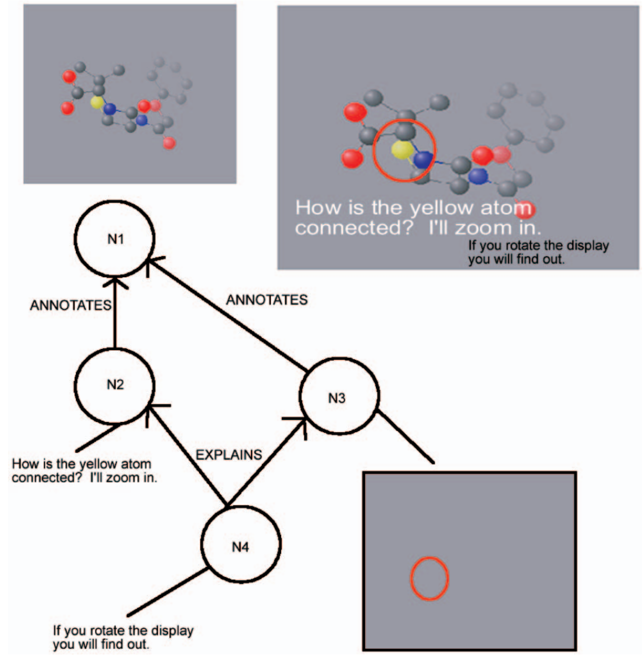

Fig. 6. In this interaction graph, the user has created two annotations for the same state and a second node attempts to explains how to answer the question posed by the user. An example of what might be displayed to the user is shown by combining the annotations with the visualization.

The prototype model manager supports annotation directly through either typed comments or recorded voice. This capability saves the visualization system the effort of performing annotation capabilities. We are working on a tablet PC-based interface to support the direct scribbling of annotations. The interaction graph displays visual cues to indicate the current position within the interaction history as well as the location of annotations.

The prototype implementation supports navigation through a direct manipulation of the graph. The user

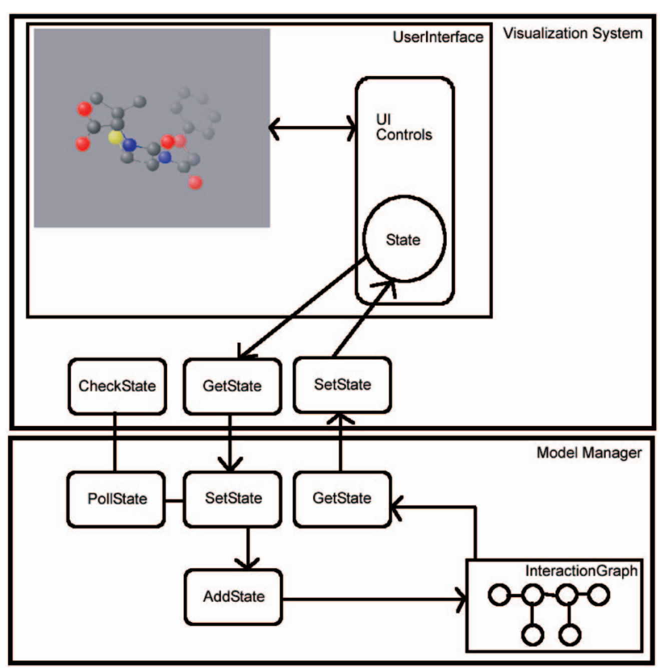

Fig. 7. An overview of the general design for the system.

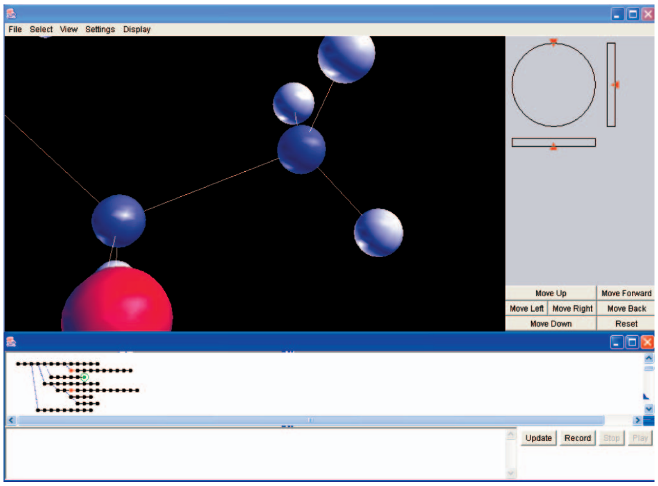

Fig. 8. The prototype that shows the interaction graph to the user.

interface supports direct navigation to a previous state by clicking on a node in the graph. The user can click on a node and then drag the mouse to replay the states in either direction, depending on the direction the mouse is moving.

It is worth pointing out that there is no restriction in the model for branching or nonlinear behavior represented in the interaction graph. However, in order for the model to support nonlinear behavior tracking, the model manager must keep track of where the user is relative to the interaction graph. The prototype supports this feature by creating branches in the graph if the current state is not a leaf node. An example graph is shown in Fig. 9. Note the use of color to provide visual cues to the user. Larger, red nodes signify the location of annotation data, while a single green node with a larger circle (bull's-eye) around the node is the current location in the graph.

The prototype system uses a directed graph data structure to manage the interaction graph in memory. When the graph is saved to disk, the data is stored in an XML document. We envision further work on this area of the system. The general approach defined by the interaction model suggests that a standard schema should be developed to facilitate interoperability between systems.

5 Evaluation and User Studies

One challenging aspect faced by evaluations of history tracking and provenance models is the nature of the problem. In particular, one thesis of this research is that history is valuable; however, the value is accretive in

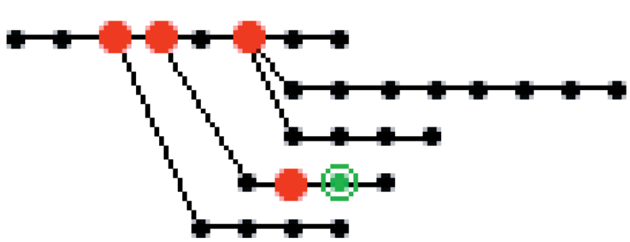

Fig. 9. This graph shows multiple branches in the interaction. The larger, red nodes indicate the location of annotation data. The green node with the bull's-eye signifies the current state of the visualization system.

TABLE 1
Demographics of the Participants in the User Study

Group	n	Male	Female	mean years exp
1	10	8	2	6
2	10	7	3	6.4
3	10	7	3	6.4

nature, which means that users would need to use such systems for long periods of time in order to derive benefits. Of course, long-running system evaluations become difficult to control.

In order to balance the need to understand the impact of our proposed technique with these challenges, we studied the interaction model implemented in two different contexts. The first implementation integrated the interaction model into a 3D molecule visualization system. The second implementation integrated the interaction model into a Web browser.

5.1 Experiment Design

There were 30 subjects that participated in the study. The participants were divided into three groups as shown in Table 1. There was no monetary compensation for participating in the study. Only nine participants had previous experience with 3D visualization concepts.

There was only one type of task given to the users: Given a 3D visualization of a molecule, identify the center of the molecule. We varied the complexity of a task by varying the complexity of the molecule, which we organized into three levels (Easy, Medium, Hard) of difficulty. Figs. 10, 11, and 12 show examples of molecules in each category.

A center for each molecule was determined in advance of the experiment, in order to judge correctness of the subject's solutions. We expected that, as the complexity of a molecule increased, users would be required to interact in more varied ways with the display in order to arrive at a

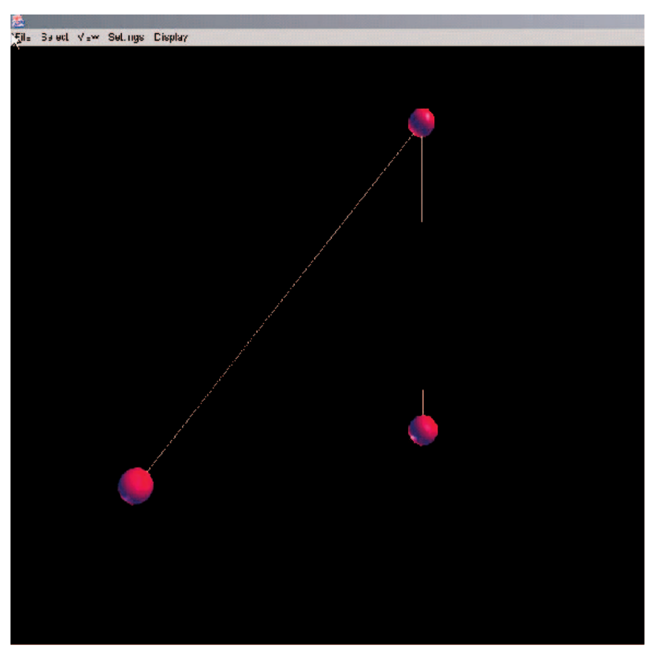

Fig. 10. A molecule categorized as "easy."

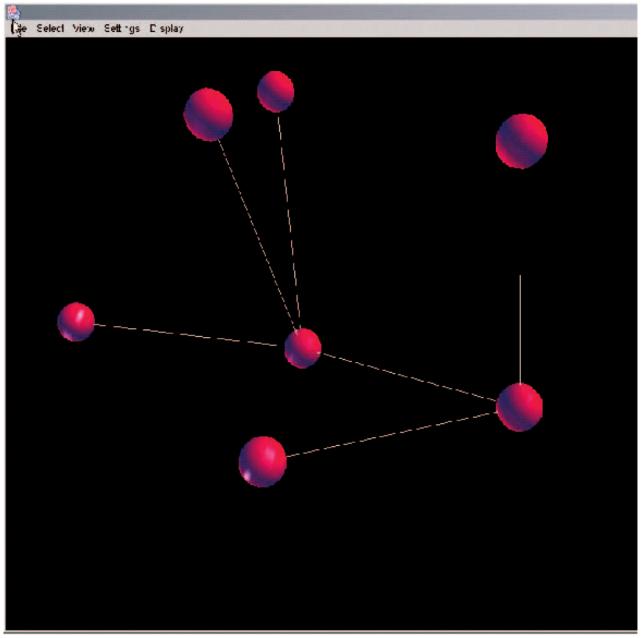

Fig. 11. A molecule categorized as "medium."

satisfactory solution. The interface supported three different view transformations: scaling, rotating, and translating of the molecule. Through the use of the tools provided to the subjects, they were to examine the structure in order to determine if a center was present. If the subject decided that a center was present in the given structure, they were to zoom in on the center node and end the task; if they decided that the structure lacked a center, they were to leave the structure as it was and indicate to the moderator that they had completed the task.

The following definitions were given to the subjects, in order for them to differentiate between the three different definitions of "center": 1) Center of Mass—the point closest to the center of the structure, 2) Articulation Point—the point connecting two structures that are approximately equivalent, 3) No center—neither a center of mass nor an articulation point can be found.

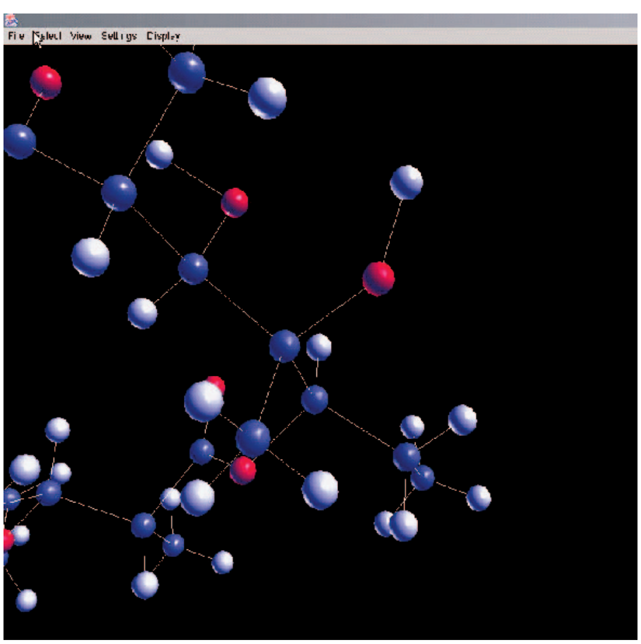

Fig. 12. A molecule categorized as "hard."

TABLE 2
Efficiency Results for the Experiment

Group	Simple	Medium	Hard	Total
1 - No History	51.34	52.14	57.30	53.60
2 - Undo/Redo History	42.01	47.96	55.68	48.55
3 - Tree History	42.43	41.49	50.22	44.71

All values are mean seconds.

Each participant was given the same 15 tasks and was required to complete them in a single session. The tasks were ordered cyclically, from easy to medium to hard, to medium, to easy, etc. After each task, the subjects were asked to report their findings by completing a survey. First, they were asked to indicate which definition of center they were using for the given task and, then, they were asked to indicate their level of confidence in their decision. These responses were recorded and used to determine the correctness of the user's responses.

Each of the user control groups used a different history-tracking technique. Group 1 used the "No History" technique, in which the user had no access to the history of their interactions. Group 2 used the "Undo/Redo" technique, in which the user could move backward to the previous state and then move forward to the next state. Group 3 used the "Tree History" technique, in which the user could directly set the state of the visualization to any previously visited state.

As the subjects interacted with the different tasks, all of their interactions were tracked and saved, creating a conceptual model of every interaction that each subject made. The information in this model included the path that the subject followed in order to come to a conclusion, how many steps the user took throughout that process, and if the task itself was completed successfully, based on the node that the user zoomed in on at the end of the task. Along with these measurements, each task was timed in order to keep track of the pattern between the amount of time spent on a task and the number of steps the subject took to complete the task.

5.2 Results

Table 2 shows the mean solution times for the different groups. The analysis of variance revealed a nonsignificant difference between the groups ($F = 2.37, p < 9.6$), with the largest difference resulting from the "Tree History" group. Combining the two history groups together and comparing to the nonhistory group results in an almost-significant difference between the groups ($t = 1.94, p < 5.3$). Fig. 13 shows the mean time per group to complete the tasks.

Table 3 shows the mean number of transformations performed while solving the tasks for each group. The high average number of interactions for the "Undo/Redo History" group provides insight into the restrictive nature of the technique. Users in this group sometimes oscillated between two adjacent states.

Table 4 shows the accuracy of each group's solutions. There was no significant difference between the groups when evaluating the accuracy of their solutions. Fig. 14 shows the mean number of correct solutions per group for each of the tasks.

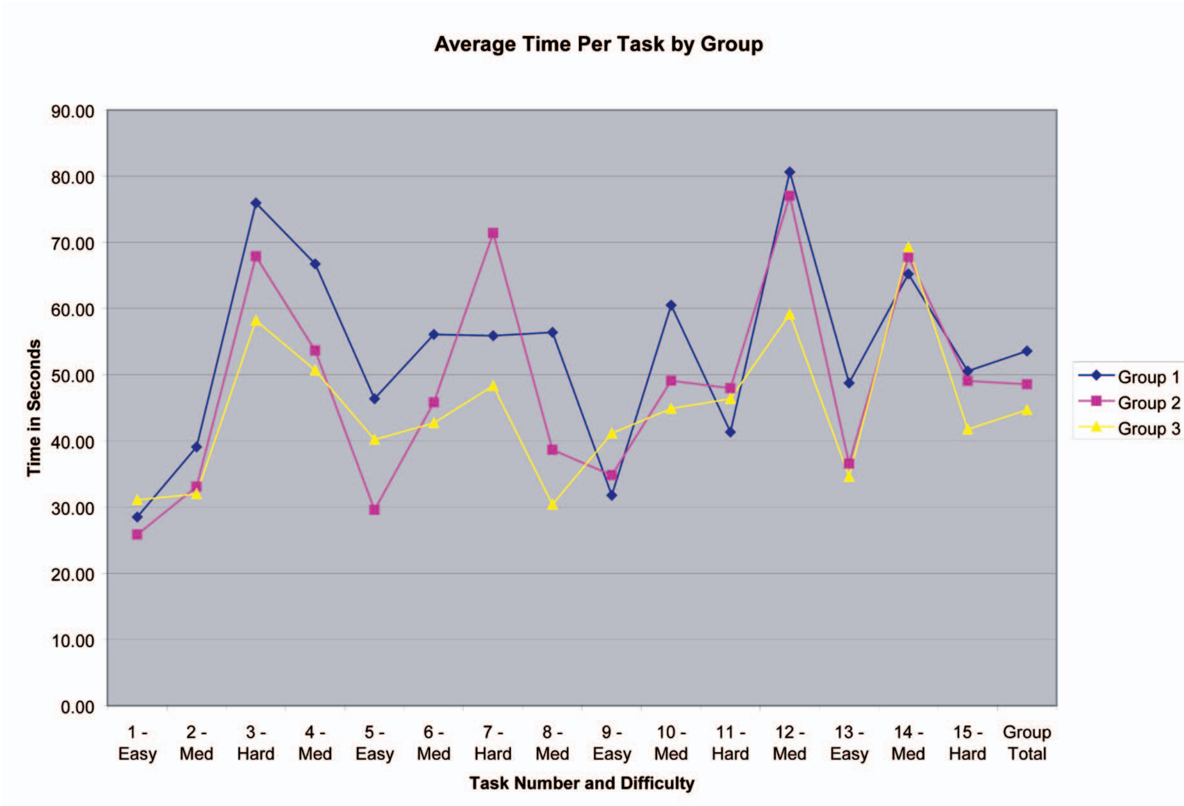

Fig. 13. Mean time to complete tasks.

The users were asked to rate their confidence in their solutions after each task. Though the differences in answers are not significant, we provide the details for each group in Tables 5, 6, and 7. Group 1 indicates an overall lower level of confidence in their solutions, especially in the "Very High" category. The larger number of "Very High" answers for the two groups with history functionality points to some effect provided by the interface. We are planning a study to specifically answer this question.

6 Application Extensions and Future Work

Our future efforts include the development of collaborative interaction tools that track multiple users' explorations of visualizations. We are exploring data mining-based techniques to provide a recommender-style guide to exploring data. We want to be careful to provide guides to data where needed without stifling individual exploration. In a broader context, we are investigating how the techniques can be employed in large-scale visual analytics applications.

6.1 Similarity-Based Representations

Similarity-based representations, rather than temporal-based representations, of provenance information present history according to a distance calculation. The distance calculations are dependent on the data that describes the state of the underlying system. For our 3D molecule visualization prototype, for example, each state is represented by a 4×4 transformation matrix.

The general Euclidean distance measure is calculated as follows: Given two equal-sized vectors $V = \langle v_1, \dots, v_k \rangle$ and $U = \langle u_i, \dots u_k \rangle$, the distance between the vectors is

$$d(V,U) = \sqrt{\sum_{i=1}^{k} (v_i - u_i)^2}.$$

Fig. 15 shows a resulting interaction graph based on this distance measure. A force-directed algorithm for drawing the graph is used. Both graph types shown in Figs. 9 and 15 are coordinated so that the user can select nodes in either graph to set the state of the visualization.

TABLE 3
Efficiency Results for the Experiment

Group	Simple	Medium	Hard	Total
1 - No History	77.18	73.60	141.12	97.30
2 - Undo/Redo History	72.68	89.46	279.42	147.19
3 - Tree History	78.28	86.34	154.62	106.41

All values are mean number of navigational steps.

TABLE 4
Accuracy Results for the Experiment

Group	Simple	Medium	Hard	Total
1 - No History	52	32	36	40
2 - Undo/Redo History	62.7	41.3	36	46.7
3 - Tree History	53.3	36	40	43.1

All values are percentages of correct answers.

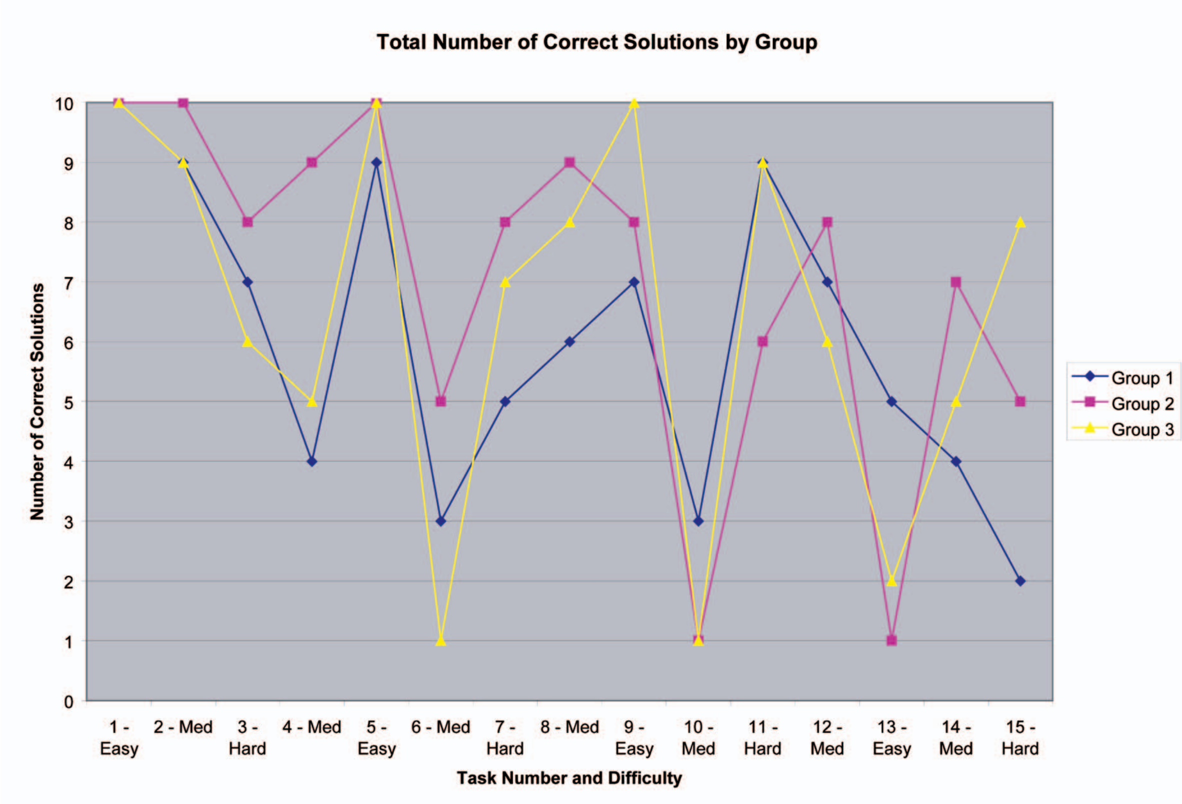

Fig. 14. Number of correct solutions per task for each of the user groups. The maximum number of correct solutions for each task is 10.

TABLE 5
Group 1 (No History) Averages for Accuracy and Level of Confidence in Solution Results for the Experiment

Task	1 - E	2 - M	3 - H	4 - M	5 - E	6 - M	7 - H	8 - M	9 - E	10 - M	11 - H	12 - M	13 - E	14 - M	15	Total
Correct	10	9	7	4	9	3	5	6	7	3	9	7	5	4	2	90
Very High	3	2	0	0	2	0	0	0	0	0	0	0	1	0	0	8
High	7	6	2	2	4	3	3	1	7	1	3	1	6	3	3	52
Somewhat High	0	2	6	6	2	6	4	5	3	7	6	4	3	3	4	61
Somewhat Low	0	0	2	2	1	1	2	4	0	2	1	4	0	4	3	26
Low	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	2
Very Low	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	1

TABLE 6
Group 2 (Undo/Redo History) Averages for Accuracy and Level of Confidence in Solution Results for the Experiment

Task	1 - E	2 - M	3 - H	4 - M	5 - E	6 - M	7 - H	8 - M	9 - E	10 - M	11 - H	12 - M	13 - E	14 - M	15	Total
Correct	10	10	8	8	10	5	8	9	8	1	6	8	1	7	5	105
Very High	5	4	0	0	5	2	2	1	3	2	1	0	5	0	1	31
High	4	3	1	1	4	4	2	2	4	1	2	1	2	4	1	36
Somewhat High	1	3	5	7	1	3	1	6	3	5	5	6	3	3	5	57
Somewhat Low	0	0	3	1	0	0	4	1	0	2	2	2	0	2	2	19
Low	0	0	1	1	0	1	0	0	0	0	0	1	0	1	1	6
Very Low	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	1

TABLE 7
Group 3 (Tree History) Averages for Accuracy and Level of Confidence in Solution Results for the Experiment

Task	1 - E	2 - M	3 - H	4 - M	5 - E	6 - M	7 - H	8 - M	9 - E	10 - M	11 - H	12 - M	13 - E	14 - M	15	Total
Correct	10	9	6	5	10	1	7	8	10	1	9	6	2	5	8	97
Very High	7	2	2	0	3	1	0	0	3	1	1	0	2	0	0	22
High	2	7	1	2	4	2	4	3	1	1	1	1	3	4	1	37
Somewhat High	0	1	3	4	1	4	1	3	6	5	3	2	2	3	6	44
Somewhat Low	1	0	4	2	1	3	5	4	0	2	5	5	2	2	3	39
Low	0	0	0	2	1	0	0	0	0	1	0	2	1	1	0	7
Very Low	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	1

6.2 Interpolation between States

Because the 3D molecule visualization states are represented by the 4×4 transformation matrix, we also implemented a method for interpolation between any two states. The user can select a starting point and an ending point for the interpolation. A popup window allows the user to specify the speed, granularity, and behavior of the interpolation. Supported behaviors include: "once"—the system flies from the starting point to the ending point and stops, "repeat"—the system flies from the starting point to the ending point and then jumps immediately back to the starting point and repeats the flight, "oscillate"—the system flies from the starting point to the ending point and then flies back to the starting point, etc.

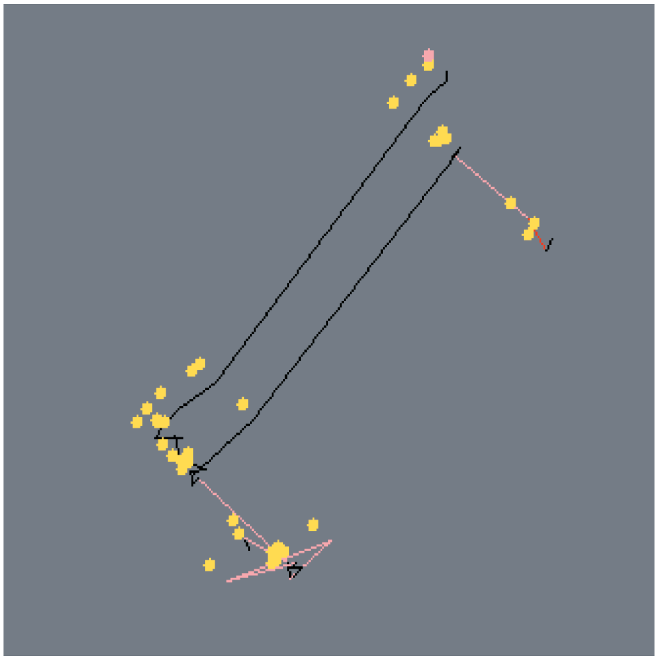

Fig. 15. This graph shows nodes mapped according to the distance between the states.

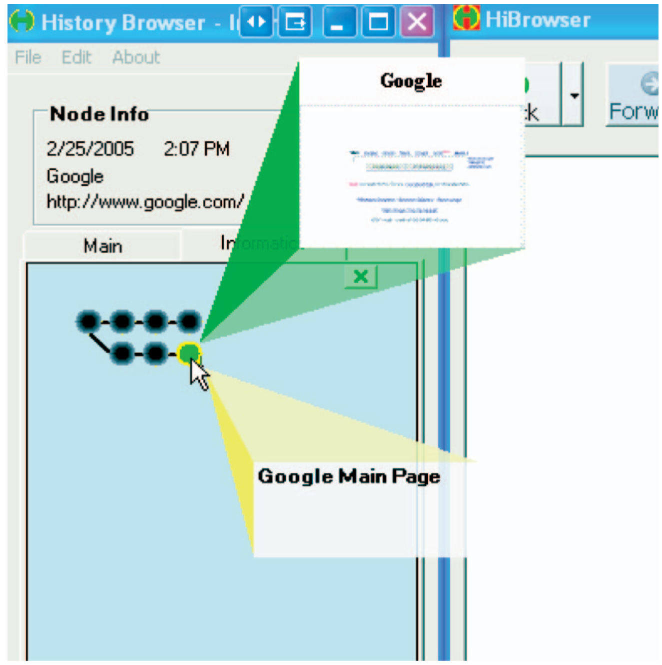

Fig. 16. The history panel shows a thumbnail of the Web page and annotations using a callout representation.

6.3 Information Foraging on the Web

Integrating the interaction graph within a Web browser takes advantage of the underlying structure of the web. While our approach is similar to previous work [2], [23], [35], [36], the focus of this project is aimed at enabling collaborators to share discovered information and the *process* of discovery [6], [30], [44].

There are several user interaction capabilities that we have implemented in the browser. When the user rolls their mouse over a node, not only does the node turn green to provide a cue to the user that they can "go" to the highlighted page, but a thumbnail image of the Web page is displayed, along with any annotations, as shown in Fig. 16.

In addition to the basic navigational design provided by the history graph, the system supports a rich set of features for editing, augmenting, managing, and sharing histories. The editing of histories is supported in a number of ways. First, users can remove individual nodes through a context-sensitive menu. Also, complete branches of the graph can be removed. Users can copy subtrees from one part of a history and insert it at another point. The system supports different tabs and history for each tab, allowing users to organize their browsing in project related areas. The prototype system supports collaboration by allowing users to save their histories into a compressed file for transmittal to another user. The recipient can simply load the received file into the history panel and take advantage of the organized history, including annotations.

We evaluated the history tracking mechanism integrated within a Web browser over a longer period of time. Six subjects were asked to install the browser and use it in place of their current browsers for a one-week period. At the end of the week, subjects were interviewed for subjective feedback. The users showed us their histories, but we did not compare histories between users. The main advantage that was consistently reported by the subjects in this small study was for "project-based" browsing. In particular, users reported the history valuable for deep-dive searches. The visual history was reported as providing a "sense of space" with which the users could maintain sense of their activities.

7 Conclusion

Because visualization systems provide a high degree of interaction, the user cannot be expected to fully document each of their interactions. We have proposed an approach to addressing this problem by augmenting exploration systems with tools to maintain the history of interactions and annotation data. The approach enhances a user's ability to communicate what they found to be interesting, as well as how they found it. Such an ability is critical to addressing visual analytics problems and is a fundamental component for systems that must provide information provenance.

Information provenance is a larger problem than even these challenging problems suggest. For example, it is possible to envision even more fine-grained tracking of user activities, such as eye tracking. Even deeper issues related to data provenance [10] abound. For example, if the underlying data is changed, our interactions may be invalid—we may be unable to find what was interesting before! Modifications to the data model may again make it impossible to recall how we found information of interest. It is not inconceivable for certain applications to require full tracking of provenance from the point in time the data was generated through each program that manipulates the data, even to the people that were involved along every step in the process.

The interaction model is the primary contribution of this work. By articulating with annotations, the model is capable of supporting a wide variety of knowledge discovery tasks. Most importantly, however, our proposed technique can be used to support collaborative discovery and recall of past explorations. Our prototypes present two different examples for how the general model can be employed. Evaluation for history tracking remains challenging due to the accretive value of history. The simple story on evaluation is that the techniques do not slow down the discovery process and do provide a simple undo/redo capability. There was some time advantage measured in our study for users that had access to their interaction histories. It is clearly the case that more long-term studies are necessary for the field to understand the impact of history and provenance tracking for visual analytics.

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