The Intuitive Power of Graph Pivots For User Exploration and Adaptive Data Abstraction

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Abstract—This paper reports on a simple visual technique that boils extracting a subgraph down to two operations—pivots and filters—that is agnostic to both the data abstraction and the size of the graph. The system’s design, as well as its qualitative evaluation with users, clarify exactly when and how the user’s intent in a series of pivots is ambiguous—and, more usefully, when it is not. Reflections on our results show how, in the event of an ambiguous case, this innately practical operation could be further extended into “smart pivots” that anticipate the user’s intent beyond the current step. They also reveal ways that a series of graph pivots can expose the semantics of the data from the user’s perspective, and how this information could be leveraged to create adaptive data abstractions that do not rely as heavily on a system designer to create a comprehensive abstraction that anticipates all the user’s tasks.

Index Terms—Information Visualization; Qualitative Evaluation; Graph Database; Graph Pivot

1 INTRODUCTION

Graph-based data systems are everywhere. Once thought of as a fallback option for data that couldn’t be finagled into a relational database, graphs are now emerging as the data format of choice, not only for overtly networked systems, such as social networks and citation networks, but also for biological systems, traffic patterns, and all of human knowledge [17, 7].

For the domain experts who will ultimately be using this data, however, graph databases offer only a new spin on an old conundrum: how to answer new and evolving questions. Obviously there are countless ways to explore graph data programmatically, but command-based queries often exceed the technical capabilities of end users. Conversely, reporting tools can provide answers to a predetermined set of frequently asked questions, but this relies on a technical expert to foresee and interpret the users’ needs.

This latter influence, in fact, is nearly impossible to erase since it is a technical expert who must impose the initial data abstraction that will dictate how all subsequent queries will be executed. This choice of abstraction, which can be highly subjective, crucially determines how the data can be used. An ill-informed choice can dramatically reduce the efficiency and accessibility of the data for the users’ most high-value tasks. It can preclude certain visualization and exploration tools from being used at all.

The ultimate goal of this work is to identify first steps towards severing the dependence of a graph’s utility on its initial data abstraction. To do this, we focus on a graph-based operation known as a “pivot.” The pivot allows users to evaluate one set of nodes in the context of some subset of its neighbors. It offers the unique advantage of being agnostic to the graph’s size and underlying abstraction, which allows it to be executed on virtually any graph.

We present a web-based graph explorer, dubbed Jacob’s Ladder, which allows users to traverse, query, and extract sub-sections of a graph using only chained sequences of pivots. We report on how the strengths and weaknesses of this tool’s design influence users’ ability to grok the underlying data abstraction. Using this tool, we are able to observe where and how ambiguity can arise in a series of pivots. We propose a “smart pivot” as a means of overcoming these natural ambiguities. Finally, we discuss the potential of graph pivots in exposing inconsistencies between the data abstraction and the users’ needs. We outline how these pivots could inform an adaptive abstraction, in which a system reshapes its schema on the fly to become more semantically relevant and efficient as questions are asked, rather than rely on a technician’s a priori intuition about what future users’ questions might be.

2 THE PIVOT

As shown in Figure 1, we define a pivot as an operation in which a user navigates from a set of seed nodes to another set of target nodes, in which every target node has a connection to any seed node. Note that the sets of seed and target nodes need not have any internal structural relationship; these sets may be arbitrarily large, and the members of each set may be entirely disconnected.

This operation can be chained together, with the target nodes from the previous step serving as the seed nodes in the current step. For example, in a simple social network of friends, the “friends of friends” for any node can be found by performing two pivots. While the pivot, by itself, creates a fairly simplistic fan-out effect, it is considerably more expressive with these common extensions:

2.1 Categorical Pivoting

A pivot does not necessarily need to swing out to all of the connected neighbors of the seed set. When a graph is heterogeneous, consisting of multiple types of nodes and edges, a pivot can swing out to only nodes of a certain type or along edges of a certain type or both. For example, in the data system for a large hospital, doctors might want to find out which other doctors their patients are seeing. By first finding themselves in the data system, they can pivot out to all of their patients, and then pivot back to all of the doctors associated with those patients.

2.2 Filtering

After any pivot, users may want to filter the subgraph of seed and neighbor nodes before the next pivot is performed. For example, instead of finding the other doctors that all of their patients are seeing, maybe a doctor only needs to find the other doctors of their female patients. In this case, the set of patient nodes can be filtered down to just the female patients before performing the second pivot back to doctors. This filtering can be based on node attributes, edge attributes, the number of incoming or outgoing edges, or any other metric that can be computed against the subgraph of seed and neighbor nodes. Filtering, as well as the categorical pivoting, make it possible to perform multiple consecutive pivots without continually increasing the number of nodes involved in each pivot, achieving a fan-in effect.

For our purposes, we will describe direct filters as those performed directly on a set of nodes, such as filtering patients nodes by their sex attribute. We will describe connective filters as those that indirectly filter a different set of nodes, such as the set of doctors being filtered by their patients’ sex.

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Pivots have made both direct and indirect appearances across the graph

visualization literature [11, 21, 18, 20, 6, 5]. While pivots have been

identified and used in the past—we do not claim the identification of pivots as a contribution—their usage is typically limited to an initial

seed node set of size one, chaining pivots together is often not sup-

ported, or pivots are used to support specific tasks on specific data

abstractions. This work explores the power and effects of graph pivots in general, ignoring any particular abstraction.

In terms of Lee et al.’s Graph Task Taxonomy [12], a graph pivot falls into three of the four identified categories. It is a topology-based operation in that it starts by identifying the neighbors of the seed nodes. It is an attribute-based operation in that it filters the neighbors to the set of target nodes. Finally, it is fundamentally a browsing operation, in that it traverses a set of $n$ paths through the graph simultaneously. As pivots are essentially an aggregate form of traversal, there is no comparison to be made to traditional instance-based techniques, such as node-link diagrams or adjacency matrices. Rather, the technique that we demonstrate could be used in conjunction with standard instance-based techniques in a linked view system. Testing our technique in isolation allows us to reflect on whether and why additional views may be necessary.

4 Why the Pivot?

There are three reasons why the pivot stands out as a potential linchpin of usable graph exploration:

4.1 Manageable Subgraphs

As graph data stores become larger and increasingly complex, the assumption that the graph can be loaded into memory and visualized in its entirety will eventually stumble. Thus, in isolation, systems such as Gephi [1], g-Miner [4], and a host of others [16, 3, 2] that rely on a holistic display of the graph, will fail to scale.

In contrast, the pivot provides a consistent and easy-to-interpret means of displaying a partial view of the underlying graph. In or-

der to perform consecutive pivots, users only need to see their current

subgraph of seed and target nodes, and the options for where they can

pivot next. As we show in this paper, novice users can extract and understand meaningful subsets of a graph by employing only pivots and filters, even though the topology of individual nodes and edges remains hidden. The pivot can be executed and visualized without having to account for the size and complexity of the entire graph.

4.2 Coverage

Before users can analyze data, they must first be able to isolate the data that is relevant to their questions. This can be a steep challenge when users do not have flexible access to the underlying data system. This work was motivated, in part, by a series of interviews with a group of bank employees who regularly interacted with a large reporting tool system. Users expressed consistent frustration with not being able to investigate connections between elements that were, in fact, connected

in the underlying data. The phrase we heard over and over again was, “I can’t get from _______ to _______."

The pivot operation addresses this difficulty by allowing movement to take place across any existing connections in the underlying graph. So long as the graph is connected, pivoting allows users to navigate between any two nodes in the system. This navigation might not precisely represent the intent of the user’s ultimate objective, but as we will discuss in subsequent sections, it can significantly narrow down the space of what that objective might be.

4.3 Abstraction Agnostic

It is easy to underestimate the subjectivity of a graph’s data abstrac-

tion [14]. Decisions must be made about what will be a node, what will be an edge, and what will be the attributes of those nodes and edges. A city, for example, could be easily viewed as an attribute of a university node (i.e. the city in which that university is located). However, it might make more sense for each city to be its own node in the graph, and for the location of a university to be represented by an edge to that city node. Flipping the notion of nodes and edges entirely can also produce a more intuitive graph [15]. The overall utility of a graph can depend heavily on how well the data abstraction matches the queries that will ultimately be run against it. We refer to these arbitrary abstraction decisions as the schema of the graph.

The advantage of the pivot is that it is a purely structural operation. It does not rely on any particular abstraction. So long as the under-

laying data structure is a graph consisting of nodes and edges, pivots can be performed. The idea of a pivot can even be applied to relation-

databases, with foreign key relationships acting as edges; with this interpretation, a pivot is equivalent to an inner join. This univer-

sal applicability can be contrasted with systems that make restrictive assumptions about what the underlying data will be and how it will be organized [11, 18, 10, 5]. These applications are immediately ruled out when a dataset doesn’t match the intended abstraction.

Pivots also have the potential to reveal the semantics of the user’s tasks. Consider the hospital example: if our doctors need to find the other doctors that their patients are seeing, they can find themselves, pivot to patient nodes, and then pivot back to doctor nodes. The series of pivots explicitly encodes the semantics of the doctor’s intent in a very simple way that could be collected to better understand users’ needs and improve the underlying data abstraction.

5 Why Not the Pivot?

The obvious drawback of formulating meaningful queries or explo-

rations by chaining together a series of pivots is that each pivot opera-

tion is atomic. A single pivot sees only the seed nodes and their imme-

diate neighbors, not the series of pivots that led up to that point. The ramifications of this limit can be illustrated by the following scenario: consider doctors who would like to know what kinds of treatments they have prescribed to patients with a particular insurance provider. The resulting sequence of pivots, shown in Figure 2, might start with doctors locating themselves in the data system, pivoting out to their patients, then pivoting out to the insurance providers of those patients.
To find patients of a given doctor that are covered by a certain insurance provider, the user starts by filtering the doctor nodes down to a single doctor. The user then pivots to patients, then to insurance providers (where another filter is applied), then back to patients. However, when the user pivots back to patients, the pivot returns all of the patients with the specified insurance provider, but not necessarily patients of the original doctor (in red).

and filtering that list down to the provider of interest. But now our doctor has a problem. Pivoting back to patients, will yield a list of all the patients who have that insurance provider, not necessarily that doctor’s patients who have that insurance provider. That next pivot doesn’t inherently understand that the pool of patients was already narrowed down and, as a result, the pivot sequence starts to diverge from the intent of the query. This difficulty can be reproduced in a system like GraphTrail [6], which only looks at a single pivot at time.

This speaks to one of our main contributions: is it possible to make these pivots smarter, so that their meaning is always unambiguous? The benefits of such an improvement are twofold. Users would, of course, have a more expressive, powerful way to query and navigate a database. Additionally, clearing up this ambiguity supports our final major contribution: the simple, unambiguous nature of a series of pivots will allow researchers and systems to collect data that directly exposes what users are actually looking for.

6. Evaluating Pivots

The critical weakness of pivots, as we have discussed, lies in the ambiguity that arises as the user traverses deeper into the graph with a series of pivots. Where does this ambiguity come from, and what could a user do to help clarify it?

To better understand the translation between real-world questions and sequences of graph pivots, we implemented the pivot operation as a web-based front-end to a Titan graph database.

6.1 Interface Design

The resulting application, dubbed Jacob’s Ladder, is shown in Figures 3 and 4. It allows users to select an initial set of seed nodes, apply filters to the set, and then pivot to a new set of connected nodes. This process can be repeated as many times as needed, with a summary of previous pivots and filters represented as lines across the top of the screen for reference. At any point, users can undo a pivot, an associated filter, or clear their history of pivots and start from scratch. As this work focuses on understanding the role of previous filters in the context of subsequent pivots, Figure 4 shows how filters can be inspected and edited individually using filter lines, or toggled across the board using a global scope button in the search bar.

The interface is designed primarily for subgraph extraction. As a user pivots through the graph, the consecutive sets of seed nodes form a smaller, more manageable subgraph that can be downloaded. Ideally, Jacob’s Ladder should be used to extract a meaningful, manageable subgraph from a large database for closer analysis in other tools, such as Gephi [1]—Jacob’s Ladder is not built to support low-level, per-node analysis. Visualizations of individual nodes and edges are deliberately omitted from its interface.

Because Jacob’s Ladder operates at such a simple, aggregate level, it completely bypasses the scale problems of traditional graph visualization systems. The required screen real estate is a function of the various types of nodes and edges in the schema of the graph, not the actual number of nodes and edges. Consequently, there is no visual limitation with respect to the actual size of the graph.

6.2 Lab Tests and Design Adjustments

The limited scope of Jacob’s Ladder presented an opportunity to study graph pivots in relative isolation. Over the course of three months, we loaded Jacob’s Ladder with a wide range of graph datasets, from IMDB’s movie graph to financial and medical data, and tested where
ences, etc. As shown in Figure 5, a diverse range of participants were
involved. Unfortunately, due to confidential data and legal complexities,
we were not able to gain access to real users in or out of their native
financial institution, and its use in a hospital database was also antici-
ployed. Initially, this system was developed for internal use within a large fi-
counter’s Ladder itself yielded this insight. Where relevant, to allow a simpler interface, the
tool reinterprets any edges as interleaving nodes. For example, if a
relationship edge in a social network has attributes, it would be re-
placed with an edge, a node containing those attributes, and another
edge. Early prototypes of the system maintained a distinction between the
two—however, the redundancy became obvious very quickly. For
the sake of simplicity, we chose to avoid additional UI elements that
differentiate between data on nodes and edges.

As we designed Jacob’s Ladder and used it to explore these datasets
in the lab, we came to develop a prediction that ambiguity only arises
in a series of pivots when the series includes both filters and cycles.

6.3 Qualitative Evaluation

To learn how users understand graph pivots, whether they are useful,
where ambiguity arises, and how pivots reveal a user’s semantic un-
derstanding of a graph, we conducted an informal, qualitative study of
users. Because we had developed some initial predictions, we were
careful to design our experiment to evaluate those predictions explicit-
ly. We were also careful to watch for trends that we did not anticipate,
including unexpected or surprising behavior.

6.3.1 Participants

Initially, this system was developed for internal use within a large fi-
cancial institution, and its use in a hospital database was also antici-
pated. Unfortunately, due to confidential data and legal complexities,
we were not able to gain access to real users in or out of their native
work environment.

Consequently, we selected a publicly available NCAA American
College Football dataset. This dataset was interpreted as a graph with
many node types, such as Players, Teams, Games, Stadiums, Confer-
ces, etc. As shown in Figure 5, a diverse range of participants were
selected, from graduate students that have experience with graph data
but minimal knowledge of football, to passionate football fans with
little to no graph exposure. Each was asked to self-report their under-
standing or expertise with regard to graph data and American football.

6.3.2 Hypotheses and Tasks

The interface of Jacob’s Ladder provided an opportunity to assess both
the power and limitations of graph pivots. Specifically, we designed
tasks that address the following research questions:

1. Can the graph pivot enable technical and domain novices to ex-
tract meaningful subsets of a large graph, even when traditional
instance-level visualizations are not included?

2. How does the technique obscure the topology of the database?

3. Does the user understand the scope of the next pivot? Is the
interface sufficient to resolve ambiguous cases?

The corresponding tasks are:

1. With minimal introduction, observe whether users can select all
the quarterbacks on a specific team (users must filter, then pivot,
then filter).

2. Observe whether users can anticipate where to find the “fumble”
attribute without help (filter, pivot, connective filter, pivot back).

3. Given a specific team, observe whether users can select the set
of teams that the seed team beat. This task requires the user to
either remove the initial filter, or toggle the global scope button
(filter, pivot, filter, toggle scope, pivot back).

It is important to note that these tasks were designed to aggressively
discover the limitations of our technique, rather than merely serve as
existence proofs of where it succeeds [9]. Consequently, we focus on
these limitations in discussing our observations, as they form the seeds
for reflection in Section 7.

6.3.3 Experiment

Each 30-minute session involved the participant and the researcher
seated at mirrored displays, each with a mouse and keyboard. In
addition to the researcher’s notes, screen capture software was used to
record the user’s actions and voice. Where necessary, participants
were first given a brief introduction to the dataset, including explana-
tions about college football and/or graph data. Participants were then
given a 5-minute introduction to the tool, including two brief demon-
strations of the system, similar to tasks 2 and 3 that the participants
would later be given. As we were particularly interested in understand-
ing whether users could decipher the scope of their applied filters on
their own, only the function of the global scope button was explained
and demonstrated; the filter lines were ignored. Next, participants
were given the three tasks in order. Finally, users were given time
to explore the data freely, and comments, questions, and discussion
were encouraged. As we were particularly interested in understanding
whether users could decipher the scope of their applied filters on thei-
own, only the function of the global scope button was explained and
demonstrated; the filter lines were ignored.

6.3.4 Task 1 Observations

All participants were able to accomplish the initial filter and pivot in
Task 1 with ease. Interestingly, while most users were able to perform
the final filter without difficulty, many users were not aware that they
had already successfully completed Task 1.

Participants navigated from Team nodes to Player nodes, and the
interface initially displayed the principally descriptive attribute of the
nodes they had selected: in this case, player names. Users would
switch the histogram to group players by their position attribute, and
then filter players by selecting the “QB,” or quarterback position. At
this point, users had technically succeeded in selecting the quarterback
player nodes, but because the histogram only displayed one “QB” bin,
they often were not aware that they were finished until they switched
back to the player name attribute.
6.3.5 Task 2 Observations

In Task 2, participants were asked to find the set of players on a team of their choice that had fumbled the ball at some point in the season. This question was difficult for all participants to perform because it required traversing from Team nodes to Player nodes, and then to Player-Game Statistics nodes. No “fumble” attribute was directly visible from the Player nodes. As such, only one participant was able to come close to successfully navigating to this set.

6.3.6 Task 3 Observations

The third task was to identify the set of teams that a team of their choice beat. This was an opportunity to observe whether users understood the scope of the filters. We specifically tracked whether participants clicked the global scope button at the correct point in the task.

While visualization of local topology is not necessary for many tasks, we also learned from participants’ performance in Task 2 that our particular implementation of the graph pivot in Jacob’s Ladder obscures the global topology of the graph—we were perhaps too minimal in its design. An even higher-level overview of the schema of the graph, such as the technique demonstrated by Van den Elzen et al. [19], is still likely necessary to help the user plan how to pivot and filter toward node types and attributes of interest, especially for unfamiliar datasets.

7.2 Delineating Where Ambiguity Occurs

Task 3 confirmed our initial predictions about where ambiguity arises. As shown in Figure 6, the meaning of a user’s pivot is always clear and intuitive for many graph visualization tasks. The tests also confirmed our predictions about where ambiguity arises in a series of pivots. Finally, the tests showed that a series of pivots can expose the user’s understanding of the semantics of the data in a way that could easily allow for a system to reshape its data abstraction based on user behavior.

7.1 When Are Other Views Needed?

Our tests confirmed Hypothesis 1, that the simple pivot operation can empower novice users to extract meaningful subsets from large graphs. Our technique circumvents the scalability issues of traditional graph visualizations by avoiding local topology altogether—we demonstrate that, for many graph data tasks, it is not necessary to render detailed node-link diagrams. Working at the aggregate level that pivots enable is often sufficient and intuitive for many graph visualization tasks.

Overall, our results support, with some qualifications, our hypothesis that the graph pivot is a powerful tool that can enable novice or disinterested users to extract meaningful subsets of the graph without visualizing low-level graph topology. The tests also confirmed our predictions about where ambiguity arises in a series of pivots. Finally, the tests showed that a series of pivots can expose the user’s understanding of the semantics of the data in a way that could easily allow for a system to reshape its data abstraction based on user behavior.

6.3.7 Incidental Observations

While the study was somewhat controlled by the tasks issued to the participants, we were careful to observe whether additional patterns surfaced. We observed some confusion between the filter functionality of the tool and the pivot functionality. Participants would sometimes go to the search box when they meant to filter, or to the filter controls when they meant to pivot. This reveals a design flaw in the Jacob’s Ladder interface: the search field technically applies a filter, as do the more traditional filter controls. Applying filters in multiple locations in the interface caused some confusion.

Another unexpected pattern that we observed was that participants would often enter a node class name, such as “Team” in the search box instead of attribute values. Because the system only expects attribute queries in the search field, it would try to find node attributes that match “Team” instead of finding nodes by class name. “Team” nodes would subsequently disappear from the menu, resulting in confusion.

Finally, we were surprised by how well the participants were able to interpret the meaning of their current selection. Particularly during Task 2, participants were observed performing long chains of pivots in search of the “fumble” attribute. Almost all participants were cognizant of the fact that they needed to be somewhere else in the graph. Impressively, almost all participants were able to articulate the meaning of their current selection when asked, even if many pivots were involved. For example, during Task 3, Participant 5 navigated from Team (Ohio State) → Team-Game Stats (WIN) → Team (failed to remove the Ohio State filter) → Game → Team-Game Stats (WIN filter still applied, grouped by team name). When asked, he correctly interpreted the visible set as any team that had won a game that Ohio State was involved in.

7 DISCUSSION

Overall, our results support, with some qualifications, our hypothesis that the graph pivot is a powerful tool that can enable novice or disinterested users to extract meaningful subsets of the graph without visualizing low-level graph topology. The tests also confirmed our predictions about where ambiguity arises in a series of pivots. Finally, the tests showed that a series of pivots can expose the user’s understanding of the semantics of the data in a way that could easily allow for a system to reshape its data abstraction based on user behavior.

7.2.1 Pivots Only

In our initial explorations of the data before the user study, the first thing we discovered was that it was impossible to create ambiguity by performing pivots alone. If no filters are enacted during a series of pivots, then the only logical outcome of the next pivot is to return all of the connected nodes of the specified category.

7.2.2 Pivots and Filters

When a filter is enacted at a certain point in the pivot sequence, it manifests in two ways. The first is as a direct filter against the category...
When this occurs, we can make an informed guess about the users’ nodes, thus they are only relevant when users return to that category. Unlike connective filters, direct filters affect only a single category of the user at every turn, we can better narrow down this problem space to a subset of them. While it is not possible to guess the exact intent of direct and connective filters that have been applied, or only intends and, if it’s the latter option, whether the user intends to retain or still only women? To which it has been applied. For example, if users want to see all of the doctors that are women in a medical database, they can group the list of doctors by a “gender” attribute, and select only the group of women. This filter is applied directly to the doctor category, and depends only on an attribute of the doctor nodes.

However, when users pivot from doctors to their patients, that gender filter against the doctor category serves a dual function as a connective filter against the patient category. This connective filter has an increasingly indirect effect on each category of nodes that is visited after the filter is applied.

Our study showed that these indirect effects were not difficult to understand. Even though users sometimes became “stuck” in their exploration of the football dataset after a long series of pivots and filters, they could still generally articulate the meaning of the nodes that they had arrived at. Additionally, so long as no category is visited more than once after the filter has been applied, the only logical outcome is still to pivot out across all of the available connections to the next category. There is no previous interaction with that next category to suggest otherwise, and thus, no ambiguity.

### 7.2.3 Pivots and Filters and Cycles

Ambiguity arises only when a given category of nodes is visited more than once after a filter has been applied. When this occurs, the revisited category is carrying with it a set of direct and/or connective filters that the user could potentially want to restrict the current pivot operation, rather than simply pivoting out across all of the available connections. For example, if we continue from our previous example, where we filtered the list of doctors to only see women, and pivoted out to patients, if we then pivot back to doctors, which doctors does the user want to see? All of the doctors associated with those patients, or still only women?

More generally, these options can be described as:

1. Perform the pivot operation normally, swinging out to all of the connected neighbors that match the specified category (Fan-out pivot).
2. Further restrict the nodes returned by a normal pivot with the previous direct and connective filters that have been applied to that category (Fan-in pivot).

### 7.3 Implications For Smart Pivots

The question then, is how to determine which of these options the user intends and, if it’s the latter option, whether the user intends to retain all of the direct and connective filters that have been applied, or only a subset of them. While it is not possible to guess the exact intent of the user at every turn, we can better narrow down this problem space to isolate the exact source of the ambiguity.

#### 7.3.1 Direct Filters

Unlike connective filters, direct filters affect only a single category of nodes, thus they are only relevant when users return to that category. When this occurs, we can make an informed guess about the users’ intent by looking at the series of pivots that were performed since the last visit to that category. If no filters were enacted during those interim pivots, then it can be assumed that the user intends to fan-out (discard the previously enacted direct filters). Otherwise, they would simply be returning to the exact same set of nodes that they previously visited, rendering that entire series of interim pivots useless.

An example is the classic search task to find the co-stars of Kevin Bacon in the IMDB movie graph. Given a list of actors, users apply a filter to just include Kevin Bacon (direct filter). Then users pivot out to the movie category to see the list of Kevin Bacon’s movies. Then, users pivot back to the actor category. If the direct filter remained in place, this list would still be limited to only Kevin Bacon, not the list of his co-stars—because the list would be redundant, we can automatically remove the filter.

In contrast, if a filter has been enacted during the interim pivots, the decision of whether to retain the direct filter remains ambiguous. In this case, it is better to err on the side of leaving the user’s filter in place, and rely on them to remove it manually if that is their intent. We predict that, in general, this kind of smart pivoting will do the right thing in the majority of scenarios.

Our tests with users confirmed this pattern. Jacob’s Ladder does not implement any “smart pivot” logic—instead, we deliberately challenged users with questions about the data that led to both fan-out and fan-in scenarios and left all control of the scope of filters up to the user. Users often failed to click the global scope button and remove filters when they needed to. However, they almost never reenacted filters incorrectly.

#### 7.3.2 Connective Filters

One of the ideas that we explored in the Jacob’s Ladder interface was how to visualize the effect of connective filters. For example, in the summary of pivots displayed across the top of the screen, we draw lines from where direct filters were enacted and extend them across all subsequent pivots. What we observed from this display was that connective filters implicitly reinvent themselves. When a user returns to a category of nodes at which a direct filter has been enacted, the connective filter associated with the previous visit to that category can be discarded. A new connective filter is then established based on the set of nodes that the user selects before pivoting out again. This new connective filter might be functionally identical to the previous one, but the point is that the system only needs to track connective filters back to the most recent visit to the category that enacted them. Thus, the number of connective filters in effect at any given point in the pivot sequence is linear with the number of node categories in the graph.

A similar realization can be made about the categories that are affected by any given connective filter. When determining whether to fan-out or fan-in, the fan-in option is equivalent to the intersection of two sets of nodes: the nodes returned by the fan-out option and the nodes that were returned when the user previously visited that category. While the user must still explicitly distinguish between fanning out or fanning in, this means that the system need only remember the users’ last visit to each category to properly perform the fan-in option.
7.4 Implications For Learning From Pivots

In addition to their potential in helping users more freely navigate graphs, pivots also present opportunities for system designers to develop adaptive data abstractions. As we have mentioned, a critical difficulty in visualization design is the inability to validate the accuracy of data and task abstractions before implementing a system [14]. A visualization designer must arbitrarily decide the structure of the data before implementing a visualization—all too frequently, system designers choose an abstraction that does not correctly anticipate users’ tasks or data, only to discover this error after significant work has been put into implementing a system.

Exposing users to purely structural operations like the graph pivot can make these misunderstandings more apparent; we saw examples of this in our study. Users were often not aware that they had successfully completed Task 1, they would often go to the “wrong” part of the interface to filter a set of nodes, and they would often type node classes in the search box, such as “Team,” instead of querying node attributes. While this behavior may have been in part due to their unfamiliarity with the interface, it makes sense that users would not immediately know whether to think of a value as an attribute of a node, a distinct node entity, an edge or hyperedge, or even a node class. These are all arbitrary decisions that may or may not correspond to the user’s expectations.

Pivots do not merely expose the arbitrary nature of certain data abstraction decisions. They can also work the other way, in that they expose what a user expects the data abstraction to be. The abstraction-agnostic nature of pivots presents an opportunity to learn about and adapt to the semantics of the data on the fly, rather than having to anticipate it completely from the start. A series of pivots is a very simple—yet explicit—indication of the data semantics from the user’s perspective. When a series of pivots is unambiguous, it creates an unprecedented theoretical possibility: a system could observe user behavior, and reshape the data on the fly to more appropriately match the users’ tasks and data.

7.4.1 Adaptive Connections

For example, suppose in the hospital database scenario in Figure 7, that doctors must frequently determine which treatments can be prescribed based on a patient’s insurance provider. However, let us assume that in the initial graph abstraction, insurance providers and treatments are only connected through patients. While pivoting and filtering make it possible to identify which treatments specific insurance companies have allowed, this is a very roundabout way of answering that question, and it encounters the somewhat complex semantics of connective filtering that we discuss above.

In this example, the system could observe users performing frequent pivots from treatments, to patients, to insurance providers, and back. When this pattern reaches a certain threshold of usage, the system could automatically add a set of edges that directly connect the insurance providers with the prescribed treatments. From usage patterns alone, a machine could automatically “invent” a new category of semantically meaningful edges, in this case, edges that indicate that a specific insurance company has covered a specific treatment in the past. These new edges would allow users to move directly between these elements and make correlations without having to pivot through the patient nodes—enhancing both the semantic relevance of the underlying data abstraction, as well as database efficiency.

7.4.2 Adaptive Attributes

Edge topology is not the only arbitrary schema decision a technical expert may make with regard to a graph data abstraction. For example, as we have discussed above, the decision whether something is a node or an attribute of a node is arbitrary, and may or may not be amenable to a user’s task. These decisions, too, can benefit from observing user behavior in the context of a series of pivots.

Suppose that administrators at a university are frequently trying to pair students with professors from their home country. Let us assume that in the initial data system, the home countries of both students and professors are stored as an attribute of those nodes.

The system could observe users frequently using this attribute to correlate these two types of nodes. In response, the system can push the country attribute of student and professor nodes out into the graph as independent country nodes, allowing users to make direct pivots between students and professors from the same country.

7.4.3 Advantages and Limitations of Learning From Pivots

The result of these alterations to the underlying data structure is that the graph can adapt to better support current and new questions. The system learns which connections hold the most valuable, real-world knowledge and exposes those connections as directly as possible. These updates can be performed automatically, either as the relevant patterns are detected, or as the processing and storage resources become available to support the added complexity. Overall, this kind of system would allow the underlying data abstraction to be improved in situ, without constant collaboration between the technical experts and the domain experts. Using this method of back-filling the database structure, the graph automatically adapts to be able to efficiently deliver what users need from it.

Of course, the broad decision to interpret the data as a graph is still an arbitrary, a priori assumption that a technical expert makes that they can not validate without implementing and evaluating a system with user testing. Learning from graph pivots only provides some wiggle room within that broad decision—the pitfall of choosing the wrong broad data abstraction remains.

Furthermore, a visualization that relies on an adaptive data structure must be somewhat general, like Jacob’s Ladder, employing general techniques such as graph pivots. Specialized visualizations that rely on dataset and domain-specific semantics, such as anticipating certain entities as nodes, and others as node attributes, will not be able to make use of this kind of approach.

The theoretical possibility of adaptive graph data abstractions, however, opens the door to similar approaches in other broad data ab-

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Fig. 7. In this scenario, doctors frequently perform connective filtering on potential treatments by the insurance companies that have covered those treatments for patients in the past. The system observes this behavior, and adapts the underlying data abstraction in response, adding direct connections between treatments and insurance companies through patients.
straction categories. It may be possible, for example, for a system to automatically derive new set definitions as users interact with general-purpose set visualization systems such as UpSet [13], or to automatically pre-compute frequent weighted attribute combinations in general-purpose ranking systems such as LineUp [8].

8 CONCLUSIONS AND FUTURE WORK
Across our lab tests and user tests, Jacob’s Ladder helped us to examine the expressive abilities and ambiguities that arise when constructing queries using sequences of pivot operations. The graph pivot is a very simple and intuitive, yet powerful operation that shows promise for the future of graph data analysis, especially as it does not suffer from scalability with respect to the size of a graph. When coupled with filtering, users with a diverse range of expertise were able to discover and extract data subsets of interest at this aggregate, categorical level.

Furthermore, while we have demonstrated visualizing local topology is not necessary for many analysis tasks, our observations suggested that an even higher-level overview of the global schema would be beneficial to help users plan where to filter or pivot. In continuing this work, we also plan to redesign the interface to better guide users through the two primary sources of ambiguity that we were able to isolate during testing.

Finally, and most importantly, we have shown how the simple nature of the graph pivot could make it possible to learn semantic information from user behavior, potentially granting visualization designers some flexibility in their initial data abstractions. Systems that adapt their underlying data structure to user queries can become more semantically relevant, as well as more efficient.

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