Origraph: Interactive Network Wrangling

Abstract
Data wrangling is widely acknowledged to be a critical part of the data analysis pipeline. Nevertheless, there are currently no techniques to efficiently wrangle network datasets. Here we introduce a set of interaction techniques that enable analysts to carry out complex network wrangling operations. These operations include deriving attributes across connected classes, converting nodes to edges and vice versa, and faceting nodes and edges based on attributes. We implement these operations in a web-based, open-source system, Origraph, which provides interfaces to execute the operations and investigate the results. Designed for wrangling, rather than analysis, Origraph can be used to load data in many forms, wrangle and transform the network, and export it in formats compatible with common network visualization tools. We demonstrate Origraph’s usefulness in a series of examples with different datasets from a variety of sources.

CCS Concepts
• Human-centered computing → Information visualization; Visualization systems and tools; • Information systems → Graph-based database models;

1. Introduction
Data wrangling—which includes cleaning data, merging datasets, and transforming representations—is an increasingly tedious and time-consuming part of data analysis [KHP+11]. Historically, wrangling was done with scripting languages such as Python, Perl, and R, or manipulation in spreadsheet tools, requiring significant computational skills. More recently, a new generation of interactive data wrangling tools instead uses visualization, interactive specification of rules, and machine learning to improve the efficiency and scale of data manipulation tasks while also providing more accessibility to a broader set of analysts [KPHH11, VW13, Tri12].

These powerful, interactive data wrangling tools, however, ignore a data type that is increasingly important: networks. While some datasets inherently represent a network that exists in the physical world, such as the connections between neurons in a brain or roads between cities, many other more abstract datasets also benefit from a network representation during analysis. The influence of social connections on obesity rates [CF07], the spread of information via a digital media platform [Bai16], or the evolution of sticky feet of geckos [HUC+17] are but a few examples. In these cases, an analyst has one, or possibly many, mental models of the data as a network but must wrangle the dataset from a (usually)
tabular form. The transformation itself can lead to new hypotheses, and thus a new network representation of the data. Although several network modeling tools support the creation of networks from tabular datasets [HP11, HP14, LNS11, LNS14], no tools yet exist to iteratively and interactively reshape the network model itself.

In this paper, we introduce Origraph, our primary contribution. Origraph is a visual, interactive network wrangling tool that allows analysts to model and reshape networks from input data in various forms. The goal of Origraph is to allow analysts to translate their data into a network representation that is most suited to answer their analysis questions. The design of Origraph is grounded in an analysis of operations for reshaping networks. Operations that are unique to Origraph are concerned with introducing new nodes, edges, or attributes based on leveraging network structures and multivariate attributes simultaneously. For example, Origraph supports an operation to introduce edges between two nodes if these nodes are connected by a path with specified properties.

Origraph is web based and open-source. It is available at https://origraph.github.io/. We validate Origraph in two complex network modeling usage scenarios with different datasets. First, we reshape a movie dataset so that we can investigate gender biases in recently popular movies. In the second usage scenario, we integrate data from various sources and build a network that allows us to investigate how money from donors influences votes in the US Senate on issues related to the war in Yemen.

2. Data and Terminology

Here we introduce terminology we will use throughout the paper. Origraph supports modeling networks with nodes and edges. Both nodes and edges can have attributes associated with them. A class defines a common set of attributes for either nodes or edges: a node class defines a class of nodes, and an edge class defines a class of edges. As Origraph treats nodes and edges as fluid concepts that can change, we use the term class to generically refer to node and edge types and items to refer to generic instances of nodes or edges. Supernodes are nodes representing a set of other nodes.

We use the term network model for the set of classes (node and edge classes) in a network. A network model describes relationships between types of nodes and edges on an abstract level and is independent from concrete instances of the classes. Concrete nodes and links make up the network topology. It is noteworthy that networks with trivial models (e.g., a single node class and a single edge class) can be arbitrarily large and complex.

Edges can be directed or undirected. Node and edge attributes can be numerical, ordinal, nominal, sets, or labels/identifiers. Attributes may also contain nested hierarchies, lists, and objects.

3. Operations

We elicited a set of operations for wrangling multivariate graphs based on a literature review and our own experience with designing network visualization tools and preparing data for visualization [MWS+10, PLS+12, PLB+13, LKP+13, PGK+16, KLS+17, NGC+18, NSL+19, BM19]. While we do not claim that this list is exhaustive, we demonstrate that the combination of these operations extends the space of transformations currently possible with graph modeling tools [LNS14, HP14]. We also compare which tools support which operations in Table 1.

We classify these operations into three categories: modeling/reshaping operations that modify the network model and network topology by introducing new node and/or edge classes in a network; item operations that modify the network topology by removing or introducing items (instances of links or nodes); and attribute operations that manipulate the attributes of, or add new, derived attributes to, existing classes.

We illustrate these operations with a simple movie network, with actors connected to movies where each has a set of attributes. We introduce a real and complex movie dataset in Section 6.1.

Note that all of these operations are designed to be rule based and are executed on the model level instead of on the instance level. That means, for example, that we exclude explicit authoring of relationships between two specific nodes, or the creation of individual nodes. Instead, we can introduce edges between nodes based on a rule. For example, we could introduce edges between actors if they were born in the same year.

### Table 1: Table of operations supported by Origraph, Orion, and Ploceus

<table>
<thead>
<tr>
<th>Modeling / Reshaping</th>
<th>Origraph</th>
<th>Ploceus</th>
<th>Orion</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Connect/Disconnect Nodes</td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
</tr>
<tr>
<td>Promote Attribute</td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
</tr>
<tr>
<td>Facet Node/Edge Class</td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
</tr>
<tr>
<td>Convert Between Node/Edge</td>
<td>yes</td>
<td>no</td>
<td>no</td>
</tr>
<tr>
<td>Project Edges</td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
</tr>
<tr>
<td>Create Supernodes</td>
<td>no</td>
<td>no</td>
<td>no</td>
</tr>
<tr>
<td>Roll Up Edges</td>
<td>no</td>
<td>yes</td>
<td>yes</td>
</tr>
<tr>
<td>Filter by Attributes</td>
<td>no</td>
<td>no</td>
<td>*</td>
</tr>
<tr>
<td>Connectivity-Based Filtering</td>
<td>yes</td>
<td>no</td>
<td>no</td>
</tr>
</tbody>
</table>

### Attribute Operations

<table>
<thead>
<tr>
<th>Operation</th>
<th>Origraph</th>
<th>Ploceus</th>
<th>Orion</th>
</tr>
</thead>
<tbody>
<tr>
<td>Change Edge Direction</td>
<td>yes</td>
<td>no</td>
<td>no</td>
</tr>
<tr>
<td>Derive In-Class Attributes</td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
</tr>
<tr>
<td>Connectivity-Based Attribute</td>
<td>Derivation</td>
<td>no</td>
<td>yes</td>
</tr>
</tbody>
</table>

Note: In this table, * refers to operations that are only partially supported, or are referred to under different names, as denoted by the superscripts. Ploceus: 1 Create Connection, 2 Create, 3 Slice n’ Dice, 4 Only for immediate neighbors, 5 Ploceus can identify specific node values through the search function. 6 Ploceus does allow for duplication of attributes across tables. Orion: 1 Link, 2 Promote, 3 Split, 4 Only for immediate neighbors.

© 2018 The Author(s)

Computer Graphics Forum © 2018 The Eurographics Association and John Wiley & Sons Ltd.
ships based on tabular data, and “reshaping” for operations that modify an existing network.

- **Connecting or disconnecting** items is the most fundamental modeling operation. Connections can be established by leveraging the primary key / foreign key approach well known in the database literature, where each item of a tabular dataset has a unique ID, and another column has a foreign key pointing to a primary key of the same or another table. This is also a common way to store graphs in non-volatile memory: many network file formats store lists of nodes and lists of links between these nodes. We also consider cases where an item in a table stores a list of connection targets using foreign keys. More generally, connections can be derived from arbitrary attributes, for example by (partially) matching strings, or by evaluating arbitrary functions on attributes. In the movie dataset, for example, we could introduce edges between movies that have a significant number of female actors, to form a clique of gender-balanced movies.

- **Promoting attributes** allows users to promote all unique values of a column in a table into a new class (Figure 2). In the movies example, we could take a column containing filming locations and promote these locations to a separate “location” class, while at the same time introducing edges between the locations and their source items. An important consideration when promoting is what to do with the attributes of the rows being aggregated. The appropriate solution, such as dropping all attributes, averaging, summing, or storing as nested lists, will depend on the data and task.

- **Faceting** slices a class based on the value of an attribute and creates new classes for each slice, as illustrated in Figure 3. An example is to facet the movie class on the genre attribute, which would generate a new class for each unique genre containing only the movies of that genre.

- **Converting between nodes and edges** transforms connected nodes into edges, or vice-versa, retaining the connectivity and semantics of the network, as illustrated in Figure 4. For example, given actors connected to movies, we convert the movie nodes to edges, which results in a collaboration graph between actors, where edges connect actors that have acted together in a movie.

- **Edge projection** introduces an edge based on a path in the network model between nodes, as illustrated in Figure 5. The path can be specified with a set of rules leveraging the classes and the attributes of the network. For example, in an actor–role–movie–production company network, edge projection can be used to connect an actor with the production company. Another example is to project edges from an actor–movie–actor relationship to an actor–actor relationship, limiting edges to financially successful collaborations by only considering edges through movies that had a box office return above a specified number.

- **Creating supernodes** for sets of nodes creates a new supernode class, where the nodes in that class inherit all the links from the constituting nodes, and are connected with new “part of” links to the constituting nodes. Figure 6 shows a network before and after a supernode was created from two of its nodes. When creating supernodes, we can also apply an aggregation function on attributes, such as summing or averaging the attributes of constituting nodes. For example, if we would like to create supernodes for movies of franchises (e.g., to aggregate all Batman movies), all actors ever playing a role in a movie of a franchise would be connected to that franchise’s supernode, and the franchise nodes would
have links to their constituting movies. Note that the described version of this operation retains all aggregated nodes and links. If retention is not desired for the final network, these nodes and links can be filtered out in a subsequent step.

- **Rolling up edges** combines parallel edges, or multiple edges that connect the same two nodes, into a single edge of a new edge type. Again, aggregation functions for attributes could be applied. For example, if an actor plays more than one role in a movie, and therefore is connected to the movie by more than one edge, rolling up these edges would result in a single edge.

### 3.2. Item Operations

Item operations change the number of items in existing classes. They may leverage the network model, but they do not modify it. Item operations affect the topology of the network, as they manipulate which nodes and edges exist.

- **Filtering by attributes** removes nodes or edges based on the values of an attribute. For example, we could filter by removing all movies that grossed less than $10$ million, or removing all actors that acted in only a single movie.

- **Connectivity-based filtering** describes filter operations on items (nodes or edges) that leverage the connectivity of a network. In the movie network, where actors are connected to movies they have acted in, an example of connective filtering is to filter all actors who have never acted in a movie that grossed more than $100$ million. Connectivity-based filtering can also leverage complex, multihop operations.

### 3.3. Attribute Operations

We define these operations as those that modify existing class attributes or create new ones, but that do not impact the network model or the network topology.

- **Changing edge direction** introduces or removes directionality into previously undirected edges, or changes the direction of edges. Like all other operations, changing edge direction is rule based. For example, in a network of movies and actors, edges between movies and actors can be made directional to represent an “acted in” relationship.

- **Deriving in-class attributes** leverages existing attributes in a node or edge class to derive new ones. For example, for actor nodes with birth and death year, we could derive the attribute “age”, representing either the actor’s current age (if year of death is blank) or their age at death.

- **Connectivity-based attribute derivation** is concerned with deriving attributes for a node or edge class based on attributes of nodes in a possibly indirectly connected class (Figure 7). As an example, in an actor-movie network, we can compute a new attribute “gender bias” on the movie class by iterating through all the actors connected to each movie and dividing the number of men by the number of women in that movie.

### 3.4. Housekeeping Operations

In addition to these data wrangling operations, a system implementing these operations will also need to enable a series of basic operations, such as importing data from various file formats, extracting nested file structures, exporting data for consumption by graph visualization tools, renaming classes and attributes, removing or hiding classes or attributes, etc.

### 3.5. Discussion

We explicitly exclude an operation of creating “superedges” by aggregating edges, because this operation would result in hyperedges, which lack widespread support in graph visualization tools.

Some of the described operations can be achieved by sequentially executing other operations. For example, **connectivity-based filtering** can be achieved by first deriving attributes based on connectivity and then filtering based on attributes. Similarly, converting nodes to edges could be achieved by first projecting edges and then deleting the intermediate nodes and edges. We have chosen to include these operations nevertheless, because we believe that these operations are closer to an analyst’s mental model and require less indirection. An implementation of these operations would certainly leverage the more basic operations.

### 4. Related Work

Origraph draws on related work in graph editing, tabular data wrangling, graph databases, and network modeling. Graph editing refers to tools aimed at visualizing and editing existing networks. Tabular data wrangling tools work with tabular data and excel at data transformation and querying. Graph databases are optimized for storing, indexing, and querying large networks. Network modeling involves extracting a network from tabular data. We discuss relevant prior work in the respective subsections below.

#### 4.1. Graph Editing

A wide array of tools are designed to allow users to visualize and edit networks and their associated attributes. Tools such as Cytoscape [SMO’03] and Gephi [BHJ09] focus on the topology of the graph and offer several editing features. Similarly, Graphviz [EGK’01] is a collection of graph drawing tools, including layout programs and customizable graph editors.

Tools in this space allow users to modify a network, mainly by creating or deleting nodes and edges. This level of editing is useful.
for tasks such as finding and correcting mistakes in the data or inputting new data. However, these edits are not rule based and hence are limited to the instance level and do not generalize to the entire network. Additionally, graph editing tools assume a well-defined network as input. They are primarily tasked with representing network models as they exist, and do not have features aimed at creating or deriving new models.

The Tulip framework [AAB*17] touches on network modeling by enabling users to import data and generating multiple data models for users to visualize and explore. However, users do not have control over how these data models are generated, nor can they modify them.

4.2. Wrangling Tabular Data

Data wrangling applications for tabular data include tools such as Google Refine [HM11], Data Wrangler [KPHH11], and Microsoft Excel, which focus on data transformation and cleanup. These systems enable analysts to reformat input data to best suit their analysis tasks, but they are not designed to support network data.

Some data wrangling tools use network visualization in the process of wrangling data. D-Dupe [BLGS06] uses a network perspective to help resolve duplicate entities while cleaning a dataset, and Schema Mapper [RCC05] uses network visualizations to explore how one hierarchical dataset maps to another. Although these approaches utilize network visualization in the wrangling process, and support wrangling tasks on non-tabular data, they do not wrangle networks themselves.

NodeXL [SSM09], an extension to Excel, allows users to import, visualize, and transform network data. However, NodeXL provides only a minimal set of network transformation features. Moreover, as pointed out by Liu et al. [LNS14], conducting extensive network reshaping with NodeXL would require users to be Excel experts.

4.3. Scripting for Graph Wrangling

Another domain of related work are graph databases. These systems are optimized for storing, indexing, and querying large networks. Specific languages have been developed to query and manipulate graphs in these databases. Similar to Origraph, graph databases such as neo4j [Inc10], OrientDB [Ori10], and GraphDB [Oma06] allow users to create and transform network models as needed. However, creating or changing a network model in such databases must be done through scripting, requiring users to be proficient in the database specific query language. In contrast, Origraph does not require programming knowledge for most operations and allows users to create and transform network models with an interactive interface.

4.4. Network Modeling

Network modeling, i.e. the concept of creating networks from tabular data, has been explored by several systems. The need for these tools arises from the frequent storage of network data as tables, containing a list of items and their associated attributes. Network modeling approaches support creating graph models from tabular data, and commonly also provide visualization to better understand and explore the resulting graph structure.

Commercial systems such as TouchGraph Navigator [Tou18] and Centrifuge [Sys18] support network modeling by allowing users to create attribute relationship graphs from tabular data. Attribute relationship graphs, which were introduced by Weaver [Wea10], refer to graphs where attributes are connected based on co-occurrence. A related approach, used by both Pivot-Graph [Wat06] and HoneyComb [vSD09], generates new network models by aggregating all nodes that have a certain attribute.

The two systems most related to Origraph are Orion [HP14] and Ploceus [LNS14]. Both systems model attribute relationships from tables from relational databases. For a comparison of supported operations refer to Table 1. Ploceus’s approach is based on relational algebra whereas Orion uses relational tables as its base and represents networks as edge tables. Although Orion and Ploceus are well suited for network modeling from tabular data, they do not support reshaping existing networks or rich edge attributes beyond edge weights. The ability to iterate on chosen data abstractions is restricted to creating a new network model from the raw data. Each distinct network model needs to be specified from the ground up; users cannot create alternative network models with an existing model as a starting point. Notably, both tools emphasize analysis of the network data within the tool, whereas Origraph is designed as a wrangling-first application, with visualization for analysis mostly used for validating wrangling operations.

Another related modeling tool is Graphiti [SPEB18], which uses demonstration-based interaction to create edges in networks. The tool infers possible data abstractions from instance-level operations. Although Graphiti supports modifying existing networks by adding new edge types, it does not support more extensive reshaping operations such as changing nodes to edges or deriving new classes from attributes of connected nodes or edges. Additionally, Graphiti is only suited to working with undirected, unipartite graphs. Origraph offers support for unlimited types of nodes and edges as well as directed edges, allowing users to connect data from multiple sources to generate a suitable network model.

Ultimately, Origraph builds on existing work by extending the concept of network modeling and providing powerful network reshaping features. In this vein, Origraph offers support for rich edge attributes, more expressive network modeling features such as faceting and deriving reduced attributes, and annotation features. Our work fundamentally differs from existing systems by giving users the ability to leverage existing network models to create more expressive abstractions for node and edges that best reflect their semantic understanding of their data.

5. Origraph

Origraph is our graph wrangling system that implements most of the operations described in Section 3 in an interactive, visual system. Origraph leverages in place manipulation in lieu of programming to provide users with the ability to model and reshape networks. We use the term in place manipulation to refer to interactions that are as close to a visual representation of data as possible,
while avoiding the stricter term direct manipulation. Another key design goal of Origraph is to immediately visualize the effect of an operation on the network model, the underlying topology, and the attributes, so that analysts can easily understand their actions.

The interface contains three main views: a network model view, an attribute view, and a network sample view (see Figure 1). The network model view is one of several ways users can modify the state of the network by generating new node and edge classes, and connecting existing classes. The attribute view shows a table for each node and edge class, where attributes are columns and rows are instances. Table headers enable users to filter, sort, control instance labeling, and generate new node classes based on attributes. The network sample view displays a sample of the network with a concrete instance of each class in the network model. Views can be flexibly placed and scaled.

5.1. Interface Design

The network model view represents the network schema as a force-directed node-link diagram. Generic classes are represented as diamonds, node classes as circles, and edge classes as lines. The number of items in the class is displayed with labels. Each class is assigned a unique color, which is used consistently across all views for elements associated with that class. Handles on each node and edge class can be used to initiate "connection" and "edge projection" operations. These interface elements give users an overview of the current schema and the ability to manipulate the schema directly. Conversion and direction changes are available in place in the network model view.

The attribute view shows a column for each class attribute. Items are displayed as rows. Column headers are the interface for initiating operations that begin with a class attribute, including promotion, faceting, direct and connectivity-based filtering, and unrolling nested structures within cells. Additional table controls support initiating in-class and across-class attribute derivation, unrolling nested structures within rows, and seeding the network sample view with rows of interest.

The network sample view shows a force-directed node-link diagram, containing a sample of the network in its current state. Although Origraph is not intended for exhaustive network visualization or analysis on its own, it is still important to give users a sense for whether their high-level modeling operations are successful at an instance level. By default, a few nodes and edges are randomly sampled from each class, prioritizing connectivity between the randomly chosen samples. Alternatively, users can seed additional nodes or edges of interest using controls in the network sample view or add specific nodes or edges of interest from the attribute view. To support inspecting individual node or edge instance attributes, the attribute view and network sample view are linked through highlighting. The labels shown in the network sample view can be changed from the attribute view.

Some complex operations, such as connection, deriving in-class and deriving attributes based on connectivity, and direct and connectivity-based filtering, use functions of network properties and/or attributes. Topology-based operations take advantage of the network model. We provide an interface that lets users specify a path across the model’s topology, shown in Figure 11. For attribute-based operations, we provide a set of standard functions, including count, sum, mean, median, mode, and concatenate, but also allow users to write custom functions, as shown in Figure 10. When users select one of the standard functions, the custom function is populated to provide a starting point for users unfamiliar with Javascript or Origraph’s reshaping library.

5.2. Implementation

Origraph’s visual interface is designed to facilitate creating a set of rules for reshaping a graph in a lightweight, flexible interface, rather than supporting visualization or analysis of the graph, or even necessarily doing all of the heavy data processing for wrangling large graphs on its own. Instead, the visual interface operates on top of an independent graph processing library called origraph.js. Ultimately, our goal is to support interactive operations with an in-memory sample of a large graph, and then export a script capable of applying users’ rules to much larger datasets.

The underlying library maintains a graph of connected table definitions, similar to a relational database—however, except for the initial raw data, all of the tables’ items and attributes are evaluated lazily, using the user-driven rules. For the in-memory, interactive wrangling scenario, lazy evaluation is important to allow free-form manipulation of those rules, and we anticipate it will also be useful for single-pass wrangling scripts working on larger data. For additional flexibility, a second graph layer exists on top of the underlying table graph that describes the network model itself—keeping these two layers separate allows for free-form reinterpretation of the underlying tables as node or edge classes.

5.3. Input and Output

As Origraph is designed as a graph wrangling tool and not a graph analysis tool, input and output are important considerations. Our design goal for input is to ingest data formats from “in the wild” data sources and to avoid the need for preprocessing. To this end, Origraph supports tabular data that can contain explicit node and link lists; alternatively links can be inferred based on attributes.

Another input data type is hierarchical, specifically JSON, which is a common format for API responses from numerous online services. The hierarchy commonly contains multiple levels of items that can be represented as nodes and edges individually. A movie object, for example, can contain an array of all cast members, themselves represented as complex objects. Origraph implements special unroll and expand operations to convert these nested structures into separate classes.

Origraph currently exports d3.js-style JSON, zipped CSV files, and GEXF for analyzing the wrangled graphs in off-the-shelf graph visualization tools such as Gephi or Cytoscape.

6. Usage Scenarios

Here we demonstrate how Origraph can be used to wrangle two different network datasets. The data for both cases was retrieved from several different APIs, and no data wrangling was performed.

© 2018 The Author(s)
outside of Origraph. The scripts used to access the API endpoints and the resulting data can be found at https://github.com/origraph/data; each dataset is also provided as a sample in Origraph. We wrangle the original data with the goal of creating network datasets that can then be imported into external network and/or tabular visualization tools, such as Gephi, for analysis. Larger versions of each figure are available in the supplemental material.

6.1. Movies Network—The Question of Gender Bias

The network used in this example is a network of movies, actors, crew members, and production companies. The data was retrieved from ‘The Movie Database’ [Com18], a community-built movie and TV database. The analysis question we want to investigate concerns issues related to gender bias in the movie industry.

We select the 50 most popular movies (according to TMDB’s internal ranking of popularity) and retrieve data related to these movies and store them in three JSON files. The movies file contains information on the 50 most popular movies, including attributes such as movie id, title and year of release, budget, genre, spoken languages, popularity, run time revenue, and nested objects describing the production companies involved. The people file contains information on all people in these movies and contains a unique id for each person and attributes such as gender, popularity, place of birth, and day of death. The credits file contains two nested objects, one for cast and one for crew. These objects contain attributes such as roles, departments, as well as the ids for the relevant movie and person. In total, the datasets contains 2689 cast items, 7704 crew items, 116 production companies, 181 relationships between production companies and movies, and 8951 people.

For each movie in our dataset, we also retrieved the Bechdel rating from [Tes18]. The Bechdel test assigns a rating from 0-3 to each movie based on three criteria: (1) the movie must have at least two women in it, who (2) talk to each other, about (3) something besides a man. A movie that fails all three criteria is assigned a score of 0; a movie that passes the test is assigned a score of 3. Supplementing the TMDB data with the Bechdel rating allows us to answer some interesting gender-related questions about the movies.

We start the process of modeling a network by importing the raw data described above. Each of the imported data files is immediately available as separate, generic classes, represented by a table in the attribute view and a diamond in the network model view. The first step in modeling the network is choosing which entities to interpret as nodes and which as edges. We start by converting generic movies to nodes.

We then select the credits table, which contains the cast and crew information as nested objects. We use the unroll operation on both cast and crew, which creates a new class for each one. Since we no longer have a need for the credits table, we delete it from our model. We are interested in using the cast and crew information to connect people to the movies they were involved in. To do that, we first convert people to nodes, cast and crew to edges, and then %connect both cast and crew to people and movies.

We then scroll through the movie attributes to “production_companies”. The values in this column are arrays of objects, so we unroll them into their own class. The unroll operation also connects the new items to the movie nodes they originated from. We rename the newly created class to “produced by” to better reflect the meaning of this class in our model.

At this stage, because the same production company is associated with multiple movies, we notice the presence of duplicate rows, showing information for the same company (see the attribute view in Figure 8).

We then select the credits table, which contains the cast and crew members, and production companies. The data was retrieved from ‘The Movie Database’ [Com18], a community-built movie and TV database. The analysis question we want to investigate concerns issues related to gender bias in the movie industry.

We select the 50 most popular movies (according to TMDB’s internal ranking of popularity) and retrieve data related to these movies and store them in three JSON files. The movies file contains information on the 50 most popular movies, including attributes such as movie id, title and year of release, budget, genre, spoken languages, popularity, run time revenue, and nested objects describing the production companies involved. The people file contains information on all people in these movies and contains a unique id for each person and attributes such as gender, popularity, place of birth, and day of death. The credits file contains two nested objects, one for cast and one for crew. These objects contain attributes such as roles, departments, as well as the ids for the relevant movie and person. In total, the datasets contains 2689 cast items, 7704 crew items, 116 production companies, 181 relationships between production companies and movies, and 8951 people.

For each movie in our dataset, we also retrieved the Bechdel rating from [Tes18]. The Bechdel test assigns a rating from 0-3 to each movie based on three criteria: (1) the movie must have at least two women in it, who (2) talk to each other, about (3) something besides a man. A movie that fails all three criteria is assigned a score of 0; a movie that passes the test is assigned a score of 3. Supplementing the TMDB data with the Bechdel rating allows us to answer some interesting gender-related questions about the movies.

We start the process of modeling a network by importing the raw data described above. Each of the imported data files is immediately available as separate, generic classes, represented by a table in the attribute view and a diamond in the network model view. The first step in modeling the network is choosing which entities to interpret as nodes and which as edges. We start by converting generic movies to nodes.

We then select the credits table, which contains the cast and crew information as nested objects. We use the unroll operation on both cast and crew, which creates a new class for each one. Since we no longer have a need for the credits table, we delete it from our model. We are interested in using the cast and crew information to connect people to the movies they were involved in. To do that, we first convert people to nodes, cast and crew to edges, and then %connect both cast and crew to people and movies.

We then scroll through the movie attributes to “production_companies”. The values in this column are arrays of objects, so we unroll them into their own class. The unroll operation also connects the new items to the movie nodes they originated from. We rename the newly created class to “produced by” to better reflect the meaning of this class in our model.

At this stage, because the same production company is associated with multiple movies, we notice the presence of duplicate rows, showing information for the same company (see the attribute view in Figure 8).

We leverage the %promote operation on the company “name” attribute to create a new class with unique company names. We then rename the newly created class to “Companies”. Figure 9 shows the state of the network model at this point. However, companies are now connected to movies only indirectly via the “produced by” nodes. Semantically, it would be more meaningful to connect companies directly to movies via an edge, which we can achieve with the %convert operation, applied to the “produced by” node class. Since Origraph supports rich edge attributes, these edges preserve all the attributes of the original data.

Next, we import the Bechdel scores, make them nodes, and link movies to their Bechdel scores based on the movie ID. However, the ID in the movie table is formatted slightly differently in these two independent datasets. We use the %derive a new attribute operation in the Bechdel table to re-format the id to match with the IDs used in the movie nodes. We need a custom function to achieve this, which we specify with the provided code editor (shown in Figure 10). Once the id columns match, we can %connect movies to their Bechdel scores, resulting in the final network model seen in Figure 1.
With the initial network model built, we are ready to reshape the network to answer the analysis questions regarding gender bias for each movie. To do this, we compute a new attribute in the movie table. Unlike the earlier attribute derivation step where we computed a new attribute within a single class, this operation requires information from connected classes, so we use the connectivity-based attribute derivation operation. In order to calculate the gender bias for actors in a movie, we must access the gender of all the people who are connected to the movie via a cast edge.

The derive attribute interface, shown in Figure 11, allows users to select which connected class to access attributes from, and provides a selection of default operations to apply. In this example, we are interested in the ratio of men to women, so we select gender from the list of attributes, and then select the advanced mode, which allows us to enter code to compute the ratio of men to women. A preview table on the right shows sample values to ensure we are computing the attribute correctly.

Once the gender bias has been computed, we sort on this attribute in the table, which reveals that of the movies in this dataset, “Ocean’s Eight” is the one with the highest ratio of women to men. Next, we are interested in seeing how the newly computed gender bias compares with a movie’s Bechdel rating, which are both proxies for understanding gender bias in movies. For that, we derive a new attribute in movie, which simply copies over the connected Bechdel rating for each movie (attribute view in Figure 1). Interestingly, the movie with the highest gender bias, “BlacKkKlansman”, passes the Bechdel test, with a score of three. This suggests that our rather trivial gender bias calculation possibly oversimplifies the concept of gender bias and does not capture the nuances of this complex subject.

A follow-up question is to find out which actors tend to be cast in movies with a lower gender bias, i.e., with a high ratio of women to men. This, however, is an exploratory question that can best be answered by visualizing the network and encoding the gender bias on the movie nodes. As stated earlier, whereas Origraph allows for basic network exploration and analysis with the attribute and network sample views, it is not meant to be used as proper exploratory data analysis tool. Hence, we export the finished network dataset and import it into Gephi for analysis, as shown in (Figure 13).

Our second use case focuses on a network of current US senators, voting behavior on the recent bill regarding US support of the Yemen war, donors of these senators, and their social media statements related to this issue. This topic has received considerable attention in the media [Maz18, Fre18] and serves as an interesting use case to demonstrate the ability of Origraph to connect data from disparate sources to tell a compelling story. The bill in question (session 2, roll call 250) was to determine whether the US should remove military support from the war in Yemen. The final vote count was in support of removing support. Yet it is still interesting to model a network that can address questions related to the votes of senators and their connections to donors. One such question is whether senators who voted against the Yemen bill were...
financially supported by a specific subset of donors with an interest in the conflict. A related question is whether senators were more or less vocal in their support or opposition, which we can estimate based on press releases and tweets.

We obtained the data from the ProPublica Congress API [Pro18] and through the Twitter API [Twi18]. Again, we did not perform any preprocessing on the datasets retrieved from these APIs. The raw data files imported in this example include: information for all current senators including gender and political party; the way each senator voted for the bill on Yemen; all press releases made by members of the senate in relation to the Yemen bill; all FEC reports about donations made in 2018 that either support or oppose a member of the senate; and all Tweets made by senators from November 28, 2018 to December 4, 2018.

Once the raw files have been loaded, we convert senators, votes, campaign contributions, press releases, and tweets to nodes. In order to connect senators to their tweets, we must first extract the twitter user information from each tweet. User information is stored as nested objects within each tweet. We generate a new class with all users by unrolling the user attribute in the tweet class, which connects the instances of the newly created user class to the original tweets. We can now connect senators to their twitter accounts based on their screen name, an attribute of the senators class. Because we ultimately care about connecting senators to their tweets, we can abstract away the twitter account class by converting it to an edge. We now have a model of senator nodes, connected directly to their tweets. The next step involves connecting senators to their votes, their press releases, and any donations made towards or against their campaign. This can be done directly with the connect interface, as Press Releases, Votes, and Donations all have an attribute that directly references the senator IDs. We are particularly interested in distinguishing between senators who voted for or against the bill, so we facet the votes node into separate “Yes” and “No” classes.

The last step in modeling this network involves extracting out the individual donation committees. Since several donations are made by the same committee, we first want to extract all unique committees from the “Donations” class. We leverage the promote operation on the “committee name” attribute which generates a new “Donor Committees” class, with edges connecting each committee to their donation in the “Donations” class.

Because we are ultimately interested in which committees support or oppose certain senators, we convert the donations node into an edge, and then facet the edge into contributions that support and those that oppose a senator.

With this network modeled (see Figure 14), we can turn to the initial questions regarding relationships between donors and vote outcomes on the Yemen bill. Our current network connects donor committees to Yes and No votes through specific senators. If we are interested in understanding the direct connection between financial contributions and votes, we can project new edges that connect donor committees directly to vote classes, shown in Figure 15. This gives us a reasonable proxy for donor interest in this issue; exporting the new projected edges, with donor and vote nodes, into Gephi allows us to explore the donor interest network, shown in Figure 15. We discover that, even though many republicans voted Yes on this bill, the NRA only supported republican senators who voted No, and opposed senators who voted Yes. Although this does not imply a causal relationship for support of that particular conflict, this could suggest a point for an analyst to investigate further.

Having incorporated Twitter and press release data, we may also be interested in whether specific senators were vocal about this issue. We can derive attributes on senators to ascertain whether their tweets contain relevant “Khashoggi,” “Saudi,” or “Yemen” strings, as well as whether or not a senator issued a press release about their vote. As we are interested in the set relationships between these new attributes, we can export the senators class to UpSet [LGS14], where we can see that, with the exception of only three senators, all senators who voted No were relatively silent about their votes.

7. Discussion

Data abstractions often change in response to evolving exploration and analysis tasks. The shape of the data is a proxy for an analyst’s real-world problem, and must be continuously assessed and refined [FM18]. We argue that transforming a dataset into the form best suited to answer analysis questions is essential, yet the tools currently available for wrangling multivariate network datasets are...
not powerful enough. The alternative of using scripting or database query languages is time consuming, requires skill sets many analysts do not have, and does not allow for rapid iterative exploration of the changes made.

Our work builds on the idea of network modeling and introduces visual, interactive network wrangling. By giving users the freedom to explore alternative data abstractions, tools like Origraph have the potential to become powerful thinking tools that could begin to address the open challenge of how to support visualization practitioners in exploring more diverse data abstractions [Mun09, BDFM14]. Although the design space of data wrangling tools is still in its infancy, it is worth considering its breadth: identifying data wrangling as a distinct category from data analysis [KHP+11] may need to be extended further to distinguish between data analysis, classical “wrangling”, and abstraction transformation. The standard notion of data wrangling [KHP+11] is often viewed through a lens of data integration, diagnosing, and cleaning data problems. In contrast, abstraction transformation is motivated by users’ mental models and hence requires a distinct set of methods that support different operations. Nevertheless, each category benefits from tight integration with the others—for example, in Origraph, visualizations of the data form a key sanity check for whether users’ reshaping operations had their intended effects.

7.1. Limitations

Although we are careful to emphasize that Origraph is not meant for data analysis or in-depth visualization of large graphs, the difference between “wrangling” and “analyzing” is fuzzy. In terms of designing data abstractions, the transformation process in itself can be considered a form of analysis. Yet, Origraph is only designed to give a faithful representation of the network model, not necessarily a holistic picture of the data. The attribute view requires scrolling to see all instances and attributes, and the network sample view uses simple sampling strategies that may not be representative of the underlying data.

We claim that Origraph removes the burden of having to use scripting for graph wrangling, yet at the same time we provide and interface for specifying advanced functions through programming. Although this may seem contradictory at first, we argue that Origraph’s standard operations and functions are sufficient for many complex use cases, without the need for programming. Scripting is only necessary where users need even more expressive logic or control, especially when dealing with attributes. Nevertheless, we plan on simplifying our scripting interface, for example, by making it more like Excel, with basic formulas, easy references to data sources, and accessible documentation.

Origraph does not support operations on tabular data that analysts have come to expect from a wrangling tool. For example, the support for cleanup and dealing with missing data is limited. We believe that such operations are better addressed in separate tools before importing tables into Origraph.

Origraph notably does not support ® creating supernodes and ℹ rolling up edges. While we plan to implement these in the immediate future, support for supernodes is inconsistent across network visualization tools. Hence, analysts using tools without dedicated supernode support will need to make decisions about which nodes to aggregate, and which nodes to remove before exporting a dataset.

Although Origraph scales to thousands of nodes and edges, it does not scale to arbitrarily large networks. We plan on addressing this using an approach common to visual data wrangling tools: loading a sampled dataset. Operations can then be applied and refined on the sample using visual inspection. After the transformation is completed, a script is generated that can be used to process a larger dataset offline, potentially leveraging cloud infrastructure.

8. Conclusions and Future Work

In its current state, Origraph and the set of operations that we have identified represent first steps toward network reshaping. Through two use cases, we have demonstrated its expressive potential. Together, these contributions have implications for data abstraction transformation tools in general.

We hope to explore and augment both the set of operations, and the tool itself, through ongoing deployment, testing, and redesign. This will include more exhaustive evaluations with users: testing and extending the tool’s usability; exploring the usefulness of each operation and what operations may be useful beyond the ones that we have identified; and identifying gaps in its expressiveness. Additionally, we plan to integrate more effective visualizations, more representative sampling, and improve scalability; to give users access to more sophisticated algorithms, such as seriated instance ordering, or clustering-based group assignments; to add provenance features to make it possible to edit, audit, share, document, and replicate users’ transformation processes; and to integrate more closely with data cleaning and multivariate graph visualization to more fully support end-to-end analysis workflows.

9. Acknowledgments

This work was funded by grants by the National Science Foundation (OAC 1835904, IIS 1350896, IIS 1751238) and by the Utah Genome Project.
References


[Inc10] Inc. N.: Neo4j, 2010.5


[Maz18] Mazá C.: Republican senators who tried to kill Yemen war resolution were paid by Saudi lobbyists. Newsweek (Nov. 2018).8


[On00] Ontotext: GraphDB, 2000. 5


