A Task Taxonomy for Network Evolution Analysis

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Abstract—Visualization has proven to be a useful tool for understanding network structures. Yet the dynamic nature of social media networks requires powerful visualization techniques that go beyond static network diagrams. To provide strong temporal network visualization tools, designers need to understand what tasks the users have to accomplish. This paper describes a taxonomy of temporal network visualization tasks. We identify the 1) entities, 2) properties, and 3) temporal features, which were extracted by surveying 53 existing temporal network visualization systems. By building and examining the task taxonomy, we report which tasks are well covered by existing systems and make suggestions for designing future visualization tools. The feedback from 12 network analysts helped refine the taxonomy.

Index Terms—Network visualization, network evolution, temporal analysis, task taxonomy, design space

1 Introduction

Network visualization is a crucial tool for understanding various network structures such as knowledge, information, biological, or social networks [1], [2], [3]. It can show the members of the networks and their relationships visually, let analysts explore the network, uncover influential actors, find helpful bridging people, or identify destructive spammers. Due to these advantages, most off-the-shelf network analysis software packages such as UCINET, Pajek, and iGraph support network visualization. Network visualization is also a core component of popular visualization programming toolkits such as Prefuse [4], Processing [5], and Protovis (or D3) [6], [7]. A Microsoft Excel extension for network visualization called NodeXL became popular by making visual network analysis easy and accessible [8].

Fueled by the rapid growth of social networks and social media [9], the interest in more powerful network visual analysis tools and methods is growing as well. One of the most pressing challenges is facilitating network evolution analysis. Many networks can be better understood when analysts can examine their dynamic nature. For example, in social network analysis, much work has been done on longitudinal network models, driven by the needs of numerous application domain problems [1], recognizing that societies evolve like living organisms because of cultural, environmental, economic, or political trends, external interventions, or unexpected events [10]. Yet most network visualization tools focus on static networks, so demand for flexible tools to analyze dynamic aspects of networks is growing.

This study proposes a task taxonomy of temporal network visualization. By establishing a comprehensive task list regarding network evolution visualization, we hope to guide the development of future tools and to encourage network analysts to pursue novel research questions. Our taxonomy has three dimensions: 1) network entities, 2) network properties to be visualized, and 3) the hierarchy of temporal features. These dimensions were extracted from 53 existing temporal network visualization systems drawn from prototypes published in academic papers, visualization resources on the web, and participants from a dynamic network visualization competition.

To review the comprehensiveness and usefulness of our taxonomy, we interviewed 12 network analysis experts from various domains including social, biology, or security network, then refined the taxonomy. The interviews allowed us to improve the initial version of the taxonomy by clarifying the ambiguous task descriptions and adding any missing tasks. Most notably, some experts pointed out that *compound tasks* needed to be more prominently represented in the taxonomy. A compound task is a combination of low-level tasks.

By comparing the task taxonomy and the systems, we can 1) identify which tasks are well covered by existing systems, 2) describe tasks that are not addressed as well, and 3) suggest the temporal features that should get more attention from future visualization system designers.

The following section reviews the related work. Sections 3, 4, and 5 explain how the taxonomy and its three dimensions were constructed. The task taxonomy is presented in Section 6 (and in more detail in the Appendix, which can be found on the Computer Society Digital Library at http://doi.ieeecomputersociety.org/10.1109/TVCG.2013.238, with the list of temporal visualization systems that were reviewed.) Section 7 presents the results of the evaluation conducted with the experts. The last section concludes the study and discusses future directions.

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2 Related Work

This study draws from previous general and temporal visualization taxonomies, then reviews time series visualization taxonomies. The selected example systems are presented with the taxonomy itself in Section 6.

There have been various attempts at constructing task taxonomies of visualization, based on different classification criteria according to task types. The first group classified the tasks by data type. Shneiderman [11] proposed a task by data type taxonomy with seven data types—one-, two-, three-dimensional data, temporal, and multidimensional data, and tree and network data—and seven tasks—overview, zoom, filter, details-on-demand, relate, history, and extract.

The second group classified the tasks as transformation operators expanding the data-centric point of view of the previous approach. Chuah and Roth [12] presented semantic primitives called basic visualization interactions (BVIs). They specified the BVI inputs, outputs, and operations. In particular, they presented a hierarchy of the BVI operations widely classified as graphical, set, and data operations. Wehrend and Lewis [13] presented a taxonomy of visualization techniques by describing (sub)problems in terms of the objects to be represented and the operations to be supported by a representation. Heer and Shneiderman [14] defined 12 interactive dynamics tasks and grouped them into three high-level categories: 1) data and view specification, 2) view manipulation, and 3) analysis process and provenance.

The third group attempted more generic frameworks by seeing the tasks as queries about function. Andrienko and Andrienko [15] suggested a generic framework for exploratory data analysis and introduced a general task typology and classified existing approaches, methods, and technologies into five categories: visualization, display manipulation, data manipulation, querying, and computation. Springmeyer et al. [16] empirically observed the scientific data analysis process from several disciplines and identified process elements such as querying for quantitative information, comparisons, applying math, managing data, and record keeping. Pillat et al. [17] analyzed multidimensional visualization tools using a taxonomy of users' tasks: identify, determine, visualize, compare, infer, configure, and locate.

In addition to these approaches that classified information visualization techniques in general, tree and graph task taxonomies are important due to their relationships to networks. Fekete and Plaisant [18] defined general tasks for trees. Shneiderman and Aris [19] defined a collection for challenges as:

1. basic networks,
2. node/link labels,
3. directed networks, and
4. node/link attributes.

They then identified eight basic tasks that could be covered by the basic networks and incrementally added more tasks according to the increase of challenge level. Lee et al. [20] presented a list of graph visualization tasks and relevant examples based on Amar et al. [21] visual analytic task list. They classified the tasks as:

1. topology based (adjacency, accessibility, common connection, connectivity, attribute),
2. attribute based (node and link attributes),
3. browsing, or
4. overview.

There have been approaches proposed in social sciences to analyze momentum, sequences, turning points, and path dependencies [22]. For example, Wasserman and Faust [1] stressed the importance of temporal social network analysis and longitudinal network models. Yet, despite the richness of general visualization task taxonomies above, we find little to address the complex tasks of *temporal* visualization analysis of graphs.

To our knowledge, three studies have suggested such classifications. Yi et al. [23] provided a temporal visualization task classification for networks and a list of measures. However, their taxonomy did not provide a complete list of temporal tasks. Palla et al. [24] listed six types of community events but did not provide a rationale or evidence to justify their classification. Hadlak et al. [25] presented a classification of visualization approaches for large dynamic graphs. They focused on two dimensions: structure and time, which they subdivided into three levels—abstraction, selection, or unreduced, so that they could create a 3 by 3 classification. However, they did not describe individual tasks. Therefore, we attempted to create a more comprehensive temporal network visualization task taxonomy with links to real example systems, then refined it using the feedback from 12 analysts.

3 Review of Systems

To build our taxonomy, we collected existing temporal network visualization systems, reviewed the temporal analysis tasks they facilitated, and organized into a meaningful structure. The initial systems were collected from three sources. First, we surveyed a visualization repository called visualcomplexity.com[1] that contained 767 visualizations (as of October 2011) from various domains such as social, knowledge, or biology networks. It was searched for temporal network visualization systems by using four queries: "Time," "Evolution," "Temporal," and "Dynamic." Each query retrieved 207, 34, six, and 83 records, respectively. They were manually examined and then 27 were selected that matched both of the two conditions below:

1. *Network visualization*—The visualized objects should be connected to each other in networks explicitly or implicitly. For example, the systems represented direct relationship links among people or concept. At the same time, some systems could mine such relationships through mining shared social tags.
2. *Temporal visualization*—They should include the time element. The systems showed temporal changes or comparison between multiple time points.

1. http://www.visualcomplexity.com.

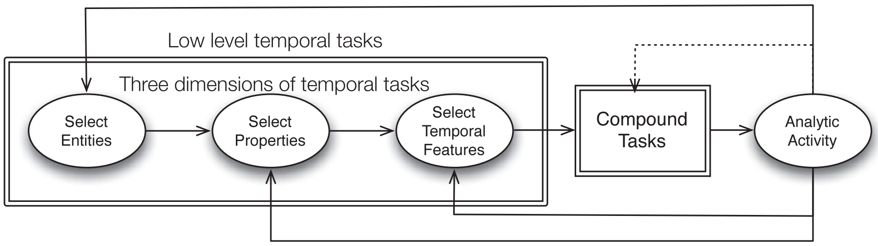

Fig. 1. Iterative process of task specification—Analysts select three dimensions to form temporal tasks (double-lined box). Throughout iterative analytic process, they refine their dimension selection and attempt to solve different tasks. Sometimes analysts can combine multiple low-level tasks to form more complicated compound tasks (dashed lines).

The second source was the IEEE VAST 2008 mini-challenge 3: Cell Phone Calls [26].[2] It is a competition to solve network evolution questions using visual analytic tools. Out of 23 participants, five teams were selected who submitted correct answers that were recognized for good visual analytic results and satisfied the two criteria above. Even though the challenge problem was identical for the five teams, they used different network tools and methods.

The third source was the three most representative information visualization conferences: IEEE InfoVis, IEEE VAST, and EuroVis. We used a query "network" to filter out network visualization research papers from the three conference proceeding database. The resulting 328 papers were manually examined to see if they satisfy the two conditions above (i.e., network and temporal visualization). We sorted out 15 papers that meet the conditions. Among them eight were already discovered from the two previous sources, so we could discover seven additional papers about temporal network visualization.

With these 39 systems as seeds, 14 more were added using a snowball sampling method [3] to locate other temporal network visualization systems based on citation networks or the authors' social networks. That is, we either found references of the seeds and followed them, or asked their authors to recommend additional new ones they knew. Finally, 53 systems were selected and they are listed in Table 3, available in the online supplemental material. Among them, 26 were prototypes included in research publications, five were the VAST'08 competition participants, and 22 were visualizations published on the web.

We stopped when the new systems only addressed tasks that had been identified using the already selected ones. The resulting taxonomy is presented in Sections 4 and 6.

4 Dimensions of Temporal Network Evolution Tasks

4.1 Definitions

Temporal network evolution tasks. By surveying the temporal network visualization systems, we identified several temporal network tasks. The generic task taxonomies in the previous section defined the tasks as operators or queries that changed the states of specific objects. Likewise, we define temporal network evolution tasks as user-initiated operations over network entities and their properties to achieve specific goals. Similarly, Roth [27] classified cartographic interaction stages as: 1) objective, 2) operator, and 3) operand.

We discovered the tasks could be described using three dimensions: entity, property, and temporal feature. Each dimension is like the operand in Roth's taxonomy. However, the three dimensions *as a whole* define the temporal tasks as goals in our taxonomy. The first two dimensions (i.e., entities and properties) reflect the nature of the tasks as for networks. The third dimension (i.e., temporal features) reflects the nature of evolution. Any single dimension alone does not produce a complete task. Even though two tasks share the same temporal features, they are considered different if they describe different network entities or properties in our taxonomy. The definitions of the three dimensions are introduced below. In the later sections, their members are introduced in detail and we will show how the temporal tasks are formed from them.

The entities are the objects analysts are interested in: node/link, group, or network. For example, analysts can be interested in node degree growth. The node is an entity whose property changes over time. The entities are not just nodes and links. Entities with different topological granularities such as groups or the entire network can be selected (Section 4.3).

Once the entities of interest are identified, the *entity properties* can be examined. They are defined as the characteristics of the entities and include both structural properties and domain properties, which can be compared over time (Section 4.4).

Finally, analysts identify the *temporal features* important for their temporal analysis task, for example, growth (Section 4.5). The temporal features are defined as the predicates [28] that change the state of the entities and the properties over time. Note that the entities and their properties are the main elements of conventional static network analysis. Analysts need to identify temporal features in addition to the entities and the properties, so that they can answer questions about network evolution.

Analysts select the entity-property-feature triples and formulate temporal tasks. We should note that they do not complete the task formulation process in one single stage. Rather, they can iterate the triple selection to work on subtasks repeatedly. The iteration can be done for all the triples or only for a part of them as in Fig. 1. During the iteration, analysts can combine independent *low-level tasks* to form larger *compound tasks* as well (Section 5).

2. http://hcil.cs.umd.edu/localphp/hcil/vast/archive/task.php?ts_id=121.

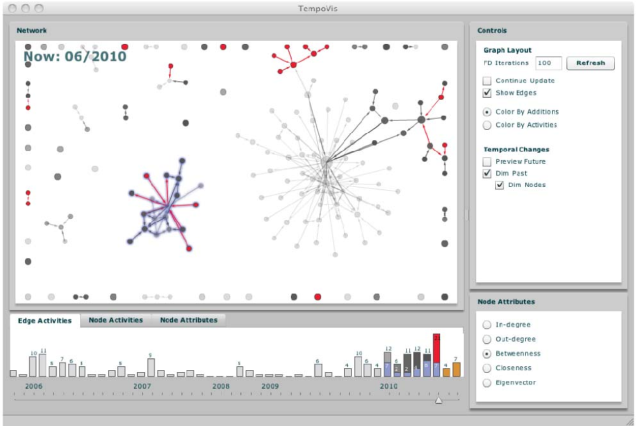

Fig. 2. TempoVis visualization for NON—an example prototype to show the evolution of a social network.

4.2 Example: Nation of Neighbors (NON) and TempoVis

An example of network and network evolution analysis illustrates the taxonomy and its dimensions. We focus on this example for two reasons. First, it is easy to understand and was the subject of two years of study [29], [30], so it can be used to explain all aspects of the temporal taxonomy in the later sections. Second, even though we worked on other communities [31] and our continuing study of twitter communities extends over many years [30], we believe that using a single example helps maintain consistency in the description of the taxonomy.

In the past two years, we have been working with the manager of a social networking service called NON.[3] NON is a web-based community network that enables neighbors to report local crime, suspicious activity, and other community concerns. It began in Jefferson County, WV, where it achieved a great success as "Watch Jefferson County." NON has expanded across the US to 230 communities (as of December 2011) [30], and we are helping the NON community managers explore and analyze the social dynamics of their social networks.

NON includes a great variety of social network data:

1. messages posted to the NON forums,
2. replies added to the original posts,
3. crime reports, and
4. e-mail invitations to the NON service.

Because NON is a local community-based service by its nature, it has physically defined communities (e.g., a town or a county).

A prototype visualization system called TempoVis was built (Fig. 2) [29] to visualize the network evolution of these four entities. TempoVis has a node-link diagram encoded with time information and timelines showing the network-level temporal events. In the node-link diagram in Fig. 2 (the largest part in the screenshot), the nodes and links that are active in the current month are painted in red and the ones that were active before the current month are gray. The intensity of the gray degrades in proportion to the corresponding node-link age. Analysts can use the time slider (beneath the timeline graph) to navigate through time to see snapshots of each month. The timeline graphs in Fig. 2 show the frequency change of the node-links over time. We use this NON network example to explain the taxonomy's dimensions.

3. http://www.nationofneighbors.com.

4.3 Entities of Analysis—Node/Link, Group, and Network

In our task specification, the visual analysis of network evolution starts from selecting an entity in various granularity: node/link, group, or network. Yi et al. [23] classified the tasks supporting the temporal social network visualization techniques into three analysis levels: 1) temporal changes at the global level, 2) temporal changes at the subgroup level, and 3) temporal associations among node and edge attributes. Sometimes analysts are interested in observing an individual player's activities but they can extend their observation granularity to a group of players or to the entire network as well.

The subgroups are defined as the intermediate meaningful entities between the entire network and individual nodes, such as triads, network motifs [32], communities [33], or clusters. They can be subdivided into two types: 1) *structural groups* and 2) *domain groups* depending on analysts' questions. The former is similar to the notion of *subgroups* in [1], where the structural positions of the members determine the groupings. The latter is closer to *social groups*, where the node property similarity determines the groupings (e.g., all members who live on a particular street). As the names suggest, structural and domain groups make explicit the mechanism by which the groups are formulated. Likewise, the network level can be classified into two types: 1) *connected network* and 2) *disconnected components*. The connected network is comprised of actors who are all connected to each other through some path; while in disconnected components members from the component are not connected to anyone in the other components. The distinction was made because disconnected components can sometimes represent one network as a whole.

NON examples. Color encoding of nodes (red and variable intensity of gray) supports the *node/link* level task analysis, while clusters represent active NON communities as *subgroups*. The timeline graph might show the evolution of the *entire network*.

4.4 Structural Properties and Domain Properties

Each entity type—node/link, group, or network—can have a number of properties that might be compared over time. We classified them as 1) *structural properties* and 2) *domain properties*. The structural properties reflect the topological relationships among the entities. They include the general graph theory-based measures that are often used for social network analysis. The latter defines information about the network entity that is independent of the network structure.

The structural property in this study is equivalent to the *topology-based property* of Lee et al.'s task taxonomy and the *basic network challenges* of Shneiderman and Aris's taxonomy introduced in Section 2. It was defined to include the temporal change of the properties that can show the topological or structural characteristics, such as degree, centrality, modularity, transitivity, and so on.

Domain properties are similar to the *attributes* in Lee et al.'s task taxonomy or *labels/attributes* of Shneiderman and Aris's taxonomy. Researchers frequently need to correlate the network structure (including its temporal change) with other dimensions and the domain properties can work as hypothetical independent or dependent variables. Examples are conversation topic, geolocation, and demographic information of actors. All structural properties and domain properties found in the 53 systems are listed in Table 5, available in the online supplemental material.

NON examples. One of the goals of the NON project was to understand the evolution of leadership of a specific member. The node betweenness-centrality can be seen as a leadership measure [34]. Another way is to look at a domain property such as the number of posts of a member, and to use it for estimating a *degree of leadership* by looking at members who have a much higher level of activity than other members [30]. The degree of leadership is a domain property of the node entities, i.e., independent of the network structure, but it can be compared with the structural properties of other nodes, such as betweenness-centrality. The number of leaders can become a domain property of the group or network. We could observe the temporal changes of various properties and compare how they evolve differently over time. There are a large number of standard structural properties and it is not the aim of this study to provide a complete list. Interested readers can refer to reviews such as [1], [2], [35].

4.5 Temporal Features

While the entities and the structural/domain properties decide *what* to analyze, the temporal features define *how* we observe, identify, or compare their states over time. They are the heart of the temporal analysis.

The temporal features were classified into two broad groups according to the data type of the temporal events that trigger the state change of entities and properties: 1) individual events and 2) aggregated events. Individual events are typically categorical occurring at separate time points, whereas aggregated events consist of an ordered set of individual time points with discrete or continuous values.

4.5.1 Temporal Features of Individual Events

1. *Single occurrences*—The atomic temporal events, for example, the addition or deletion of an entity (e.g., a link) is a single event temporal feature.
2. *Replacement*—Replacement could be seen as a deletion and a simultaneous addition; however, this task is different from an independent pair of sequential deletion and addition because they take place at the same time. Exemplary replacement events are the edge direction change or conversion to bidirectional.
3. *Birth* or *death*—This is a hybrid case as it is a temporal feature of a single entity (e.g., a group) and it occurs at a single time point but it is calculated from the temporal features of other entities (e.g., addition of nodes and links) during the entity's *life span*. Even though they are individual events, they assume a life cycle of a specific entity. Therefore, simple addition or deletion of links are not considered as "birth" or "death" of links but observing the start and the end point of a network cluster's life cycle is included in this category.

4.5.2 Temporal Features of Aggregated Events—Shape of Changes

Aggregated events span multiple time periods. They can correspond to a set of individual events (e.g., the total number of link additions can be counted for each month) or the change of a specific property (e.g., continuous network degree fluctuation over time). When one plots those numbers, a meaningful discrete or continuous shape might appear. We identified five shape of change features. For generic time series analysis, Gregory and Shneiderman [36] described three classes but we added two more temporal features for the network analysis:

1. *Growth or Contraction*—These can show whether an entity property increases or decreases over time (e.g., a community's average number of posts per member per month). It can also be aggregated from temporal features of multiple individual events. For example, the network growth might be defined as the number of node/link additions per month. They typically involve counts and statistics.
2. *Convergence or divergence*—A property can grow or contract during its initial stage but gradually becomes stable. Conversely, a stable property can become unstable.
3. *Stability*—There is no or little change over time.
4. *Repetition*—The repetition of specific patterns over time. It can *fluctuate* or show *ritual* behaviors.
5. *Peak* or *Valley*—Whether an entity property increases or decreases abruptly and then returns to its earlier value.

4.5.3 Temporal Features of Aggregated Events-Rate of Changes

While the previous temporal features were categorical and represent the type of change, other temporal features are needed to quantify the rate of changes. Moody et al. [37] called this *relational pace* and defined three different aspects: levels (fast, slow), change (accelerating, decelerating), and stability (cascades, jumps and starts). We kept the first two aspects here but moved the stability into the previous section, i.e., *shape of changes*:

1. *Speed*—This represents the amount of change in a given time period.
2. *Acceleration* or *Deceleration*—These represent the rate of change of speed, for example, some communities grow faster every month.

NON examples. Static analysis could characterize the leadership distribution across the communities in NON, while temporal evolution analysis would characterize the leadership change over time. Analysts may want to find communities that had stable leaders from the beginning, emphasizing *stability*, and compare them to communities whose leadership emerged over time, focusing on *growth*.

TABLE 1
Compound Tasks Extracted from the 53 Examples (Using Paternò's Temporal Feature Notation, Ordered by the Number of Examples per Each Compound Task Category)

$\bullet$: Node/link task, $\otimes$: Subgroup task, $\bigcirc$: Network task

Keys	Example Count	Task Notation	Notes
GeoTemporalNet, MobiVis, Pranja, SocialAction, SocialDyamicVis (VAST challenges)	5	$\bullet\gg\otimes\gg(\otimes\vert[]\vert\otimes)$	Identify interesting node properties/groups and track their changes, compare identified group changes
iQuest, MatrixFlow, TecFlow	3	$\otimes\vert[]\vert\otimes$	Compare multiple group property changes over time, Compare experimental/control group growths
SoNIA-1, SoNIA-2	2	$\bullet\vert\vert\vert\otimes\gg\bigcirc\gg\bigcirc$	Correlate node properties and network state changes
Fleming	1	$\bigcirc\vert\vert\vert\bigcirc$, $(\bigcirc\vert[]\vert\bigcirc)$	Observe individual networks and compare
SoNIA-3	1	$\bullet\vert\vert\vert\bigcirc\gg\bigcirc$	their temporal evolution

Analysts might also want to observe the *rate* of leadership change as they move from being a reader of the posts to being a leader in a community (*convergence to the leader state*) [38].

5 Compound Tasks

Thus far, we have discussed low-level tasks that deal with single event in a temporal evolution. While defining the low-level tasks is important, analysts usually combine those tasks into compound tasks to explore more complex questions. The network experts we interviewed stressed the importance of the compound tasks (Section 7) and we found several occurrences of compound tasks in the 53 systems. Paternò et al. [39] presented operators that can describe the temporal relationships among tasks. We used the operators to describe the six compound tasks found in our 53 systems. Using the notation, we could clearly see which compound tasks were more frequently used and thought to be important by analysts:

- T1 ||| T2—*Interleaving*. The actions of T1 and T2 can be performed in any order.
- T1 |[]| T2—*Synchronization*. T1 and T2 synchronize on some actions to exchange information.
- T1 $\gg$ T2—*Enabling*. T1 activates T2.
- T1 []$\gg$ T2—Enabling with information passing.
- T1 [> T2—*Deactivation*. One action of T2 occurs T1 is deactivated.
- T1*—*Iteration*
- T1(n)—*Finite iteration*. T1 iterates n times.
- [T1]—*Optional task*. T1's performance is not mandatory.
- T—*Recursion*. The task includes itself.

Table 1 lists them in a descending order according to the number of systems they were used in. Please note that we used the symbols ($\bullet$, $\otimes$, $\bigcirc$) only for the entity dimensions in the third column for simplicity. Interestingly, the most frequent compound task is comparing temporal changes of multiple group properties. In five systems, it is the main compound task after tracking/selecting the temporal changes of interesting entities or groups. In three systems, it is the sole task.

The network experts we interviewed noted two compound tasks that reflected common scientific logic are particularly important: inference and comparison/correlation. We can confirm that these compound tasks appeared frequently in the 53 examples (Table 1) as well:

1. *Inferential compound tasks*—Analysts can be interested in testing hypotheses between independent (IVs) and dependent variables (DVs). It is not simply computing descriptive statistics of temporal changes but finding relationships between those changes. The difference from the conventional inferential analysis is that either IV or DV is included in temporal tasks. Using Paternò's notation, this task can be written as $T_{IV} \gg T_{DV}$ (enabling).
2. *Comparative/correlational compound tasks*—Even when no potential cause and effect need to be investigated, analysts might be interested in comparing or correlating the temporal changes of multiple entities. In NON, analysts visually compared the growth of multiple communities to find the ones that grew more vigorously. In Paternò's notation, it is T1 |[]| T2 (synchronization).

In both cases, the tasks might require aggregated events to be generated and their temporal position compared either visually or statistically.

NON examples. Sociologists tracked a community leadership metric change over time (looking for growth, contraction, or stability) and correlated those changes to independent variables that were either temporal (e.g., community size) or non-temporal (e.g., region). They also correlated the online forum conversation topics and the activity changes to see if the increase of crime-related topics would lead to an increase of community size over time.

Analysts also wanted to know if the appearance of some aggregated events (such as peak events) preceded, followed, or happened at the same time as the appearance of some other significant aggregated events (e.g., the peaks of new users joining the community). While visual inspection was sufficient for our small data sets, creating aggregated objects that can be manipulated as additional entities in the analysis would facilitate both visual and statistical analysis of larger data sets.

6 List of Tasks and Design Space

6.1 List of Tasks

The three dimensions discussed in the previous section (entity, property, and temporal feature) help structure the long list of network evolution analysis tasks obtained from the 53 systems (see Appendix, available in the online supplemental material). Three tables complement the list:

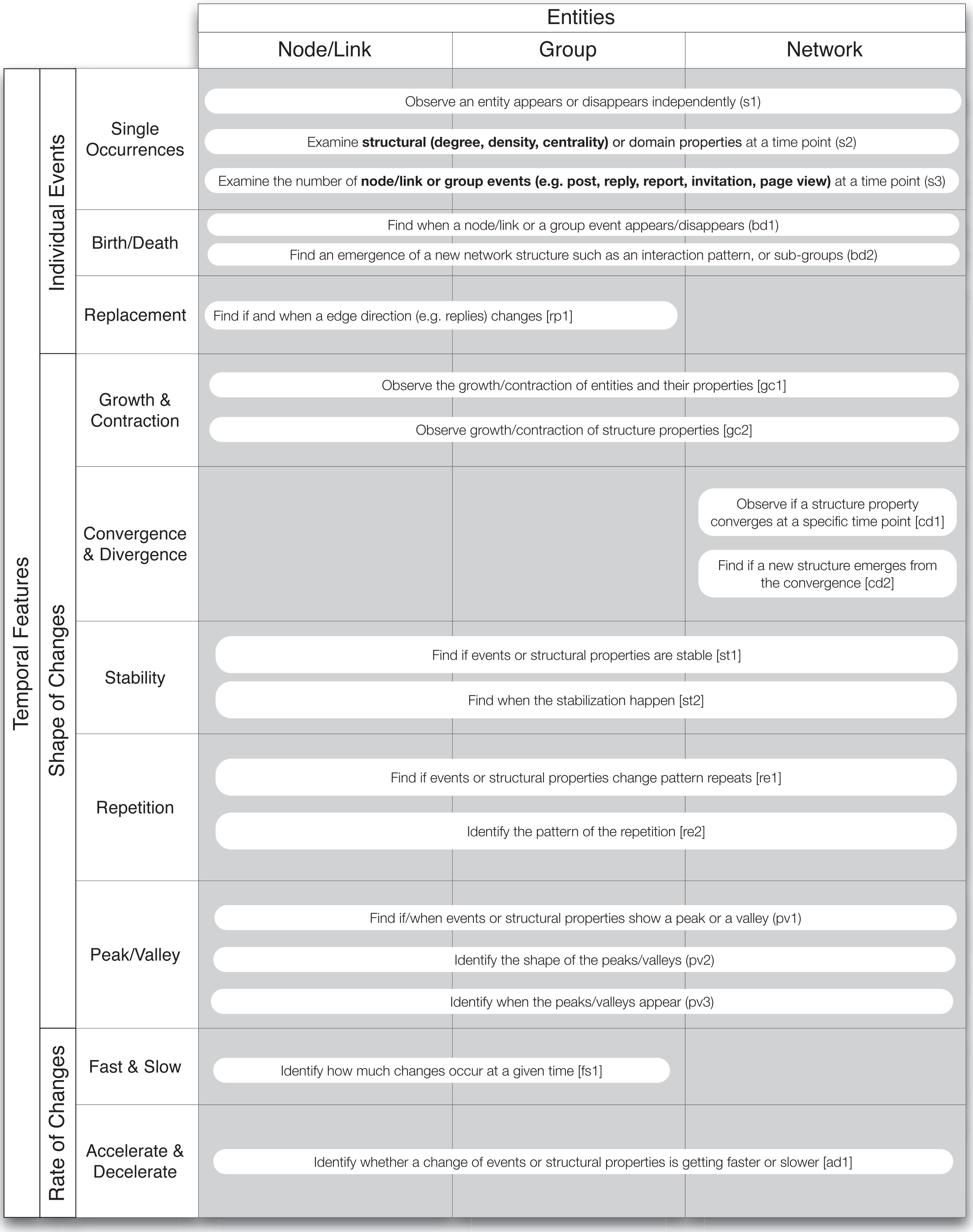

Fig. 3. A design space view of network temporal evolution tasks. The gray cell indicates no task was assigned to the corresponding entity feature. In addition to the low-level tasks in this design space, compound tasks (Section 5) allow more complex questions to be answered.

Table 3, available in the online supplemental material, shows the 53 systems, along with the application domain they were mapped to. Table 4, available in the online supplemental material, shows the temporal features used in the systems, and Table 5, available in the online supplemental material, shows the entity properties they use (structural properties and domain properties). The system keys are provided in the leftmost columns for cross referencing between the tables.

6.2 Design Space

A compact design space representation (Fig. 3) derived from our 53 example systems is more practical for designers to use. Design spaces have been used successfully in the

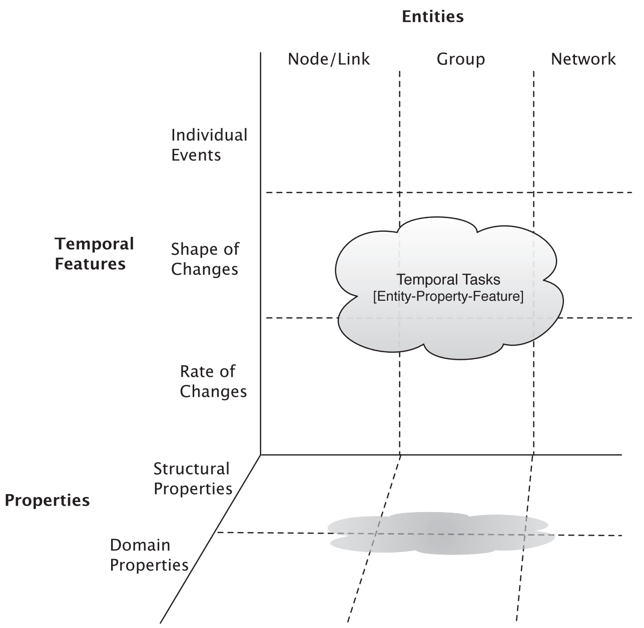

Fig. 4. A design space showing the three dimensions of the task taxonomy: entities, properties, and temporal features.

past [40], [41], [42] in a variety of situations. One interesting case is the taxonomy of input devices by Card et al. [40]. Using the design space, they could explain the individual nature and the relationships of the input devices, and could suggest what future input devices might get built by examining the empty spots where no device existed yet.

The design space of the temporal network visualization tasks (Fig. 3) shows two dimensions: entities (X-axis) and temporal features (Y-axis). The cells contain temporal tasks in white boxes. The gray cells indicate where no task was assigned. They can provide hints for unexplored temporal tasks and can suggest future tasks as Card and Mackinlay's design space did. It should have included three dimensions (as in Fig. 4) but after trying multiple possibilities, we found it too confusing. Therefore, the third dimension (i.e., structural properties versus domain properties) was not shown in the design space. The structural properties and the domain properties table (Table 5, available in the online supplemental material) is representative and sufficient to guide designers in selecting useful properties.

6.3 Design Opportunities

By examining the network evolution design space and our list of tasks we can: 1) learn what are the tasks that are commonly addressed by existing systems, and 2) identify tasks that are not addressed yet. We can summarize the lessons learned as follows:

Domain properties prevail—Almost all tasks incorporated domain properties (Table 5, available in the online supplemental material). This is rather intuitive because hypotheses usually include special domain properties and network evolution as dependent and independent variables (or vice versa).

Temporal features less explored—By mapping the tasks addressed by the systems and the temporal features (Table 4, available in the online supplemental material, and Fig. 3), we can identify the empty spots in the table or the design space (where the example was placed) and get clues about possible future additions. The most noticeable empty space is *rate of changes*. According to our knowledge, Durant et al. [43] and Morris et al. [44] were the two researchers who explicitly mentioned the rate of changes (speed) for temporal network visualization. For non-network time series visualizations or nonvisualization studies, it is not a new topic (e.g., [45], [46]) and the value of this feature for network visualization was already noted by Moody et al. [37]. Yet the temporal network visualization systems that were reviewed have not supported this feature much.

Individual versus aggregated events—Almost all systems used the individual events as they are the most basic elements that should be analyzed. The aggregated events were explored less frequently, except for simpler ones such as growth and contraction.

Low-level versus compound tasks—The examples we surveyed showed relatively lesser use of compound tasks (Table 1) than low-level tasks. We see this as an important future design opportunity even though it has not been very actively explored yet, as the experts we surveyed stressed the importance of the compound tasks (Section 7).

Multiple granularity of analysis—A lot of systems covered more than one type of entity. Yet they were mostly node/link level analyses and accompanied the network level analysis as a simple sum of the node/link level observations. Few studies attempted to provide analysts with means to control the granularity of visual analysis that can span the node/link, group, and the global network level.

6.4 Data Manipulation Tasks

While other researchers have included data manipulation tasks such as retrieve value, filter, and compute derived value in their analytic tasks (e.g., Amar et al. [21]), we excluded them in the design space to emphasize the *temporal features* of the network itself. Still, those data manipulation tasks should be supported for exploratory analysis. Below are three temporal data manipulation tasks:

1. *Select and/or aggregate time scale*—This is a basic task used repeatedly [47]. Selecting whether the visualization time interval should be monthly, weekly, or daily influences many of the decisions. Sometimes, instead of simply selecting a specific time interval, analysts need to aggregate low-level time scales into a larger time scale. For example, hourly data may need to be aggregated into daily or monthly data.
2. *Filter or sample*—These select a smaller time range from the entire data set (e.g., the last month only) or sample discrete time points from the continuous data (e.g., Sundays only).
3. *Align*—This selects a reference time point to which the remaining time points will be aligned. Alignment makes the timescale become relative instead of absolute [48].

7 Evaluation with Network Analysis Experts

7.1 Procedure

To test and improve the quality of the taxonomy, we interviewed 12 domain experts conducting research in sociology, social computing, social media, biology, and security. The taxonomy can be used in other domains but we chose the domains where the network analysis is currently of interest to many researchers. The domain experts ranged from PhD graduate student researchers to professors in the domain areas and included professional practitioners with 2-20 years of experience. With the help of the experts, we seek to answer the following questions:

1. *Comprehensiveness*—Would the experts think some tasks were missing in the taxonomy?
2. *Easiness*—Is the taxonomy easy to understand?
3. *Precision*—Does the taxonomy describe precisely the tasks?
4. *Usefulness*—Can the taxonomy be used by analysts to organize and clarify their tasks?
5. *Discoverability*—Does the taxonomy help analysts discover new tasks they had not thought of?

The first question is most important because if a taxonomy is not comprehensive enough, it will miss meaningful tasks and its usefulness be lower. To test these questions, the interviews took the following steps:

1. Ask the participants to list their own research questions on temporal network evolution.
2. Ask them to compare their list and the task taxonomy (presented to them in a textual list as in Appendix, available in the online supplemental material) and the design space (Fig. 3) format.
3. Ask them to find matching areas of the taxonomy with their own tasks and mark the degree of matching using the 9-point Likert scale. If they find no match, ask them to record the tasks.
4. Go back to the initial questions to review any missing, newly discovered, or unclear questions.
5. Grade the taxonomy in terms of five subjective assessment measures using the 9-point Likert scale.

The interviews took from 60 to 90 minutes, eliciting interest and support for our effort.

7.2 Results

The 12 experts proposed 51 research questions and then matched the questions with the tasks in our taxonomy. The evaluation was conducted with an earlier version of the taxonomy, so we report how the taxonomy was refined in response to the problems encountered during the evaluation.

7.2.1 Analysis of Comprehensiveness

Overall, experts were positive about the comprehensiveness. They could find the tasks from the taxonomy that matched their own research questions. Yet there were two exceptions:[4]

1. Inferential analysis between an entity and entity properties—"*I would like to analyze the relationships of the network evolution and the domain properties of the entities I am interested in.*"
2. Comparative analysis across multiple entities—"*I would like to compare the evolution of multiple network entities, such as the growths of community one and community two.*"

4. They rated the early version of the taxonomy that did not include compound tasks.

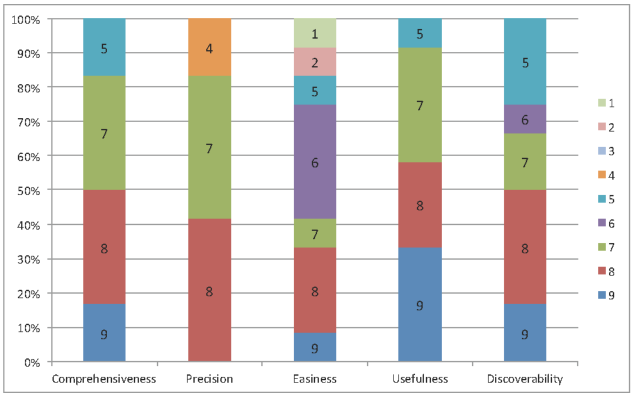

Fig. 5. Subjective feedback from network analysis experts on the taxonomy.

The two participants who were concerned about these issues gave relatively lower scores (5, where 9 is the high value) (Fig. 5, leftmost column). They pointed out that the temporal analyses of network evolution frequently needed to find out complex relationships among *low-level* temporal tasks, such as the inferential or comparative analysis described above. They are not simple sequences of independent tasks. In the initial version taxonomy, we had designed it to best represent all the possible low-level tasks. The *compound tasks* (Section 5) in our taxonomy were most similar to the complex tasks the experts mentioned. Therefore, we went back to our systems and searched the 53 examples for more complex compound tasks. The compound tasks found in the examples are listed in Table 1.

7.2.2 Analysis of Task Distribution

After confirming the comprehensiveness of the taxonomy, we examined the entities and temporal features that the participants were interested in. It is like observing that areas in the design space (Section 6.2) were picked up more frequently. A similar trend could be observed from the systems used for constructing the taxonomy (Table 4, available in the online supplemental material) but this process also showed the experts' potential tasks.

Table 2 shows the results with the degree of matching from 1 to 9 in separate columns. The top temporal features in the high match range (7-9) were *growth/contraction*, *birth/death*, *stability*, and *single occurrences*. In the mid match range (4-6), *speed*, *stability*, *peak/valley*, and *growth/contraction* were favored. This result was unexpected because the top temporal features included less frequent ones covered by the systems in Section 6. They were *peak/valley* and *speed*. It suggests that those temporal features have enough potential to be exploited in the future, even though we could not find many existing examples so far.

7.2.3 Analysis of Subjective Feedback

Fig. 5 shows the subjective feedback from the participants on five aspects of the taxonomy. As discussed in Section 7.2.1, the majority of them (83 percent) agreed on the comprehensiveness (scores 7-9). The remaining 17 percent gave five out of nine but they were all concerned about the compound task issue, rather than suggesting new temporal features.

TABLE 2
Task Distribution of Experts by Temporal Feature

	High Match (7–9)	Mid Match (4–6)	Low Match (1–3)
Individual Event Features			
Single Occurrences	43	7	4
Birth/Death	45	4	8
Replacement	25	4	2
Shape of Changes			
Growth/Contraction	53	12	11
Convergence/Divergence	31	8	12
Stability	41	22	5
Repetition	26	9	11
Peak/Valley	28	16	7
Rate of Changes			
Speed	28	16	4
Accelerate	26	5	4
Total	346	103	68

Most of them (more than 80 percent) rated positively (scores 7-9) on the *precision* and *usefulness*. Around 70 percent rated the taxonomy positively regarding the *discoverability*. They were neutral on the *ease of use*. More than 40 percent still rated positively (7-9) but around 40 percent of them gave mid-range scores. Two participants rated negatively. It was due to the confusion on some temporal features. For example, *single occurrences* and *birth and death*, which the participants had difficulty to distinguish from each other. Therefore, the descriptions of the corresponding entries were improved to clarify the meanings and highlight the differences.

8 Conclusions and Future Work

This study proposes a task taxonomy for visual analysis of network evolution. We structure the definition of the tasks using three dimensions—entity, property, and temporal feature—and identify the elements of each dimension. This task taxonomy, based on 53 existing visualization systems, identifies the temporal features utilized so far and discovers new aspects for future development. The task taxonomy provides several lessons:

1. the importance of domain properties,
2. temporal features less explored, which can guide the designers as future design opportunities,
3. higher propensity to implement the simpler individual temporal features,
4. relative propensity to low-level tasks in existing systems but the importance and the future design opportunity of compound tasks, and
5. the potential of methods for integrating different granularity of analysis into a single framework.

We tested the initial version of the task taxonomy by interviewing 12 network analysis experts. The goal of the evaluations was to assure the comprehensiveness of the taxonomy and its other proposed advantages including the ability to help researchers to develop new ideas. As a result, we gained support for the comprehensiveness of the taxonomy and improved the initial version by incorporating the feedback from the evaluation participants.

We believe that the lessons learned from the task taxonomy can help to improve future network evolution visualization systems by suggesting what missing features need to be added. For example, we are planning to incorporate more diverse domain properties into the TempoVis [29] system for NON. At the same time, it will be one of our future challenges to efficiently combine the variety of temporal features discovered in this study and provide a well-integrated user interface.

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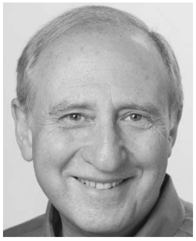

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