A Task Taxonomy for Network Evolution Analysis

Jae-wook Ahn, Catherine Plaisant, and Ben Shneiderman

Abstract—Visualization has proven to be a useful tool for understanding network structures. However the dynamic nature of social media networks requires powerful visualization techniques that go beyond static network diagrams. In order to provide strong temporal network visualization tools, designers need to understand what tasks that users have to accomplish. This paper describes a taxonomy of temporal network visualization tasks. We identify the (1) entities, (2) properties, and (3) a hierarchy of temporal features, which were extracted by surveying 44 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 9 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]. A Microsoft Excel extension for network visualization called NodeXL became popular by making visual network analysis easy and accessible [7].

Fueled by the rapid growth of social networks and social media [8] 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. Societies evolve like living organisms because of cultural, environmental, economic, or political trends, external interventions, or unexpected events [9]. In social network analysis, much work has been done on longitudinal network models, driven by the needs of numerous application domain problems [1]. Most tools focus on static networks, so demand for flexible tools to analyze dynamic aspects of networks is growing.

This paper 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 44 existing temporal network visualization systems drawn from prototypes published in academic papers, visualization resources on the web, and participants from a visualization competition.

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. In order to review the completeness and usefulness of our taxonomy, we interviewed 9 network analysis experts, then refined the taxonomy.

The following section reviews the related work. Sections 3 and 4 explain how the taxonomy and its three dimensions were constructed. The task taxonomy is presented in Section 5 (and in more detail in Appendix A with the list of temporal visualization systems that were reviewed.) Section 6 presents the evaluation results conducted with the experts. The last section concludes the paper and discusses future directions.

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2 Related Work

This paper draws from previous general and temporal visualization taxonomies, then reviews time series visualizations. The selected systems are presented with the taxonomy itself in Section 5.

There have been various attempts at constructing taxonomies of visualization, based on different classification criteria. Shneiderman [10] introduced seven data types – one-, two-, three-dimensional data, temporal and multi-dimensional data, and tree and network data – and seven tasks – overview, zoom, filter, details-on-demand, relate, history, and extracts – in order to classify information visualization systems. Card and Mackinlay [11] attempted to understand the differences among existing information visualization designs and suggested new possibilities using the design space. Chi [12] used the Data State Model which incorporated three dimensions: Data Stages, Data Transformations, and Within Stage operators. Tweedie [13] classified visualization techniques according to their externalization or interactivities. Pfitzner and others [14] unified multiple factors such as data, task, interactivity, skill level, and context into a single classification framework.

In addition to these approaches that classified information visualization techniques in general, tree and graph task taxonomies have been proposed. Fekete and Plaisant [15] defined general tasks for trees. Shneiderman and Aris [16] defined a collection of 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 and Plaisant [17] presented a list of graph visualization tasks and relevant examples based on Amar et al.'s visual analytic task list [18]. 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.

These visualization taxonomies help describe general analysis tasks, but we find little to address the complex tasks of *temporal* visualization analysis of graphs. On the other hand, there have been approaches proposed in social sciences to analyze momentum, sequences, turning points, and path dependencies [19]. For example, Wasserman and Faust [1] stressed the importance of temporal social network analysis and longitudinal network models, but not in the visualization context.

Time series visualization in general can help analysts discover relations and patterns [20] or learn from the past to predict, plan, and build the future [21]. Many tools have been proposed for time series analysis. For example, Hochheiser and Shneiderman [22] introduced timeboxes to specify query constraints on time series using direct manipulation. TimeSearcher [23], [24] provided an interactive pattern search. Aris et al. [20] focused on unevenly-spaced time series. Similan [25], Lifelines [26] and Lifeflow [27] provided methods to understand temporal categorical patterns.

To successfully apply the lessons from the time series visualization to network evolution visualization, one has to identify which temporal tasks analysts need to accomplish. We begin by studying which aspects have been implemented in existing tools and organize them by a classification scheme. To our knowledge, three studies have suggested such classifications. Yi et al. [28] 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. [29] listed six types of community events but did not provide a rationale or evidence to justify their classification. Hadlak et al. [30] presented a classification of visualization approaches for large dynamic graphs. They focused on two dimensions: structure and time, which they sub-divided into three levels – abstraction, selection, or unreduced, so that they could create a 3 by 3 classification. However, they did not describe individual tasks. We built on these studies to create a more comprehensive temporal network visualization task taxonomy and links to systems, then refined it using the feedback from 9 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 two sources. First, we surveyed a visualization repository called visualcomplexity.com[1] that contained 767 visualizations (as of October 2011). It was searched for temporal network evolution systems by using four queries: "Time", "Evolution", "Temporal", "Dynamic." Each query retrieved 207, 34, 6, and 83 records. They were manually examined and then 27 were selected that match the following two conditions.

1) *Network Visualization* – The visualized objects should be connected to each other in networks explicitly or implicitly. For example, the systems represented linked relationships among people or concepts.
2) *Temporal Visualization* – They should include the time dimension. The systems showed temporal changes or comparison between multiple time points.

The second source was the IEEE VAST 2008 mini-challenge 3: Cell Phone Calls [31] .[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. Even though

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

the challenge problem was identical for the five teams, they used different network tools and methods.

With these 27+5=32 systems as seeds, 12 more were added using a snowball sampling method [3] to locate other temporal network visualization systems using the social network of the authors. We either found references of the seeds and followed them, or asked their authors to recommend additional new ones they knew. All 44 systems are listed in Table 2. Among them, 17 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 5.

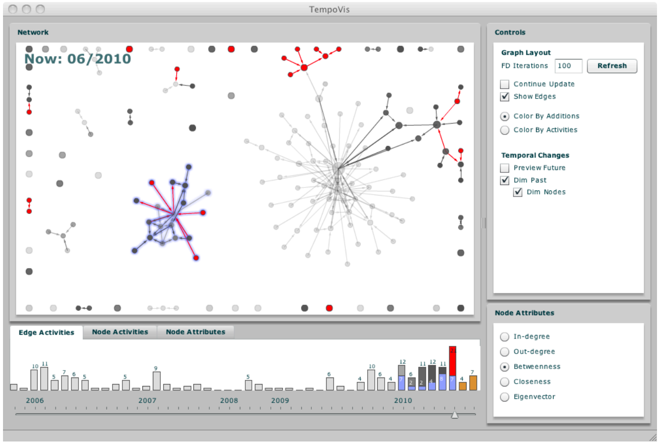

Fig. 2. TempoVis visualization for Nation of Neighbors

4 Dimensions of Temporal Network Evolution Tasks

By surveying the temporal network evolution systems, we identified that the tasks covered by them were described using three dimensions: Entity, Property, and Temporal Feature. The entities are the objects analysts are interested in: node/link, group, or network. For example, analysts can be interested in the node (entity) degree (property) growth (temporal feature) while observing the age (property) of each node. Different granularities could be adopted when selecting the entities (Section 4.2). Once the entities of interest are identified, the entity properties can be examined. The properties include both structural properties and the domain attributes, and can be compared over time (Section 4.3). Finally, analysts identify the temporal features important for their temporal analysis task, e.g. growth (Section 4.4). Note that the entities and their properties are the main elements of the conventional (static) network analysis. Here analysts formulating their task need to identify the temporal features of interest to answer their question about the network's evolution.

For the entire analysis task, analysts can iterate the triple selection to work on sub-tasks repeatedly. The iteration can be done for all the triples or only for a part of them as in Figure 1. During the iteration, analysts can combine independent tasks to form larger compound tasks (Section 5.4), too.

4.1 Example: Nation of Neighbors and TempoVis

An example of network and network evolution analysis illustrates the taxonomy and its dimensions. In the past two years we have been working with the manager of a social networking service called Nation of Neighbors (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 U.S. to 137 communities (as of February 2011), 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 the nature, it has physically defined communities (e.g. a town or a county).

A prototype visualization system called TempoVis was built (Figure 2) [32] 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 activities. In the node-link diagram in Figure 2 (above), 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 grey. The intensity of the grey degrades in proportion to the corresponding node-link age. Analysts can use the time slider (below the timeline graph) to navigate through time to see snapshots of each month. The timeline graphs in the figure (below) show how the frequency of the node-link activities change over time. We use this NON network example to explain the taxonomy's dimensions.

3. http://www.nationofneighbors.com

4.2 Entities of Analysis – Node/Link, Group, and Network

The visual analysis of network evolution starts from the granularity or the level of analysis selection. By selecting a different granularity, analysts can analyze different levels of temporal activity of networks. Yi et al. [28] classified the tasks supporting the temporal social network visualization techniques into three analysis levels: (1) temporal changes at the global

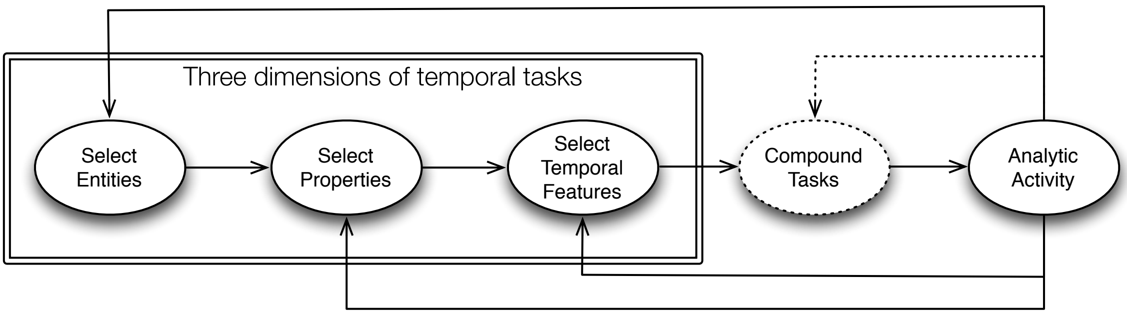

Fig. 1. Iterative process of task specification

level, (2) temporal changes at the subgroup level, and (3) temporal associations among nodal and dyad level attributes. Sometimes analysts are interested in observing individual player's activities while extending their observation scopes to a group of players or to the entire network. In NON, color encoding of nodes (red and variable intensity of grey) supports the *node/link* level task analysis, while clusters represent active NON communities as *subgroups*. The timeline might show the evolution of the *entire network* of activities.

The subgroups are defined as the intermediate entities between the entire network and individual nodes, such as triads, network motifs [33], communities [34], or clusters. They can be sub-divided into two types: (1) **Structural Groups** and (2) **Domain Groups**. The former is similar to the notion of *Subgroups* in [1] where the structural positions of the members determines the groupings (e.g. the group of NON members who actively reply to each others' posting). The latter is closer to *Social Groups* where the node attribute similarity determines the groupings (e.g. all members who live on a particular street). The terms 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 others through some path; while in disconnected components members from a group are not connected to anyone in the other groups.

4.3 Structural Properties and Domain Attributes

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 Attributes**. 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.

Lee and Plaisant [17] defined a graph visualization task taxonomy and classified the tasks as (1) Topology-based (adjacency, accessibility, common connection, connectivity, attribute), (2) Attribute-based (node and link attributes), (3) Browsing, and (4) Overview. Shneiderman and Aris [16] defined a collection of challenges as (1) Basic networks (2) Node/Link labels, (3) Directed networks, and (4) Node/Link attributes. They then identified eight basic tasks that can be covered by the Basic networks and incrementally added more tasks according to the increase of challenge level. The Structural Property in this paper is equivalent to the Topology-based property of Lee's task taxonomy and the Basic network challenges of Shneiderman and Aris's taxonomy.

The Structural Property was defined to include the temporal change of the properties that can show the topological or structural characteristics, such as degree, centrality, modularity, transitivity, etc. In NON, we used betweenness-centrality of the users participating in the online-forums (postings and replies) to find communities and leaders as in [35]. We also observed the node degree change in the conversation network to study the member activities (out-degree) and looked at the popularity of a specific member as indicated by the number of replies s/he received (in-degree). There are a large number of standard Structural Properties and it is not the aim of this paper to provide a complete list. Interested readers can refer to social network analysis literatures [1], [2], [36].

Domain Attributes are similar to the *attributes* in Lee's task taxonomy or *labels/attributes* of Shneiderman's taxonomy. Researchers frequently need to correlate the network structure (including its temporal change) with other dimensions and the Domain Attributes can work as hypothetical independent or dependent variables. Examples are conversation topic, geo-location, and demographic information of actors.

In NON, the betweenness-centrality of a node is a Structural Property of the node and can be seen as a leadership measure [35]. Another way is to look at a Domain Attribute such as the number of posts of a member, and to calculate a *degree of leadership* by looking at members who have a much higher level of activity than other members. The degree of leadership is a Domain Attribute 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 Attribute of the group or network. All Structural Properties and Domain Attributes found in the 44 systems are listed in Table 4.

4.4 Temporal Features

While the Entities of Analysis and the Structural Properties/Domain Attributes are about deciding *what* to analyze, the temporal features define *how* we observe, identify, or compare them over time. They are the heart of the temporal analysis. For example, 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*. 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*) [37]. The temporal changes such as *growth, stability, rate, and convergence*) are the heart of the temporal analysis and are defined as Temporal Features.

The temporal features were classified into two broad groups according to the data type of the events they relate to: (1) Individual events and (2) Aggregate events. Individual events are typically categorical events occurring at separate time points, whereas aggregated events consist of ordered set of individual time points with continuous values.

4.4.1 Temporal features of Individual Events

1) **Single Occurrences** – The atomic temporal events, e.g. the addition or deletion of an entity (e.g. a link) is a single event temporal feature.
2) **Replacement** – Replacement can be defined as a deletion and a simultaneous addition. Other replacement events are the edge direction change or conversion to bi-directional.
3) **Birth** and **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 simple 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.

4.4.2 Temporal Features of Aggregated Events – Shape of Change

Aggregated events span over 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 continuous change of a specific property (e.g. continuous network degree fluctuation over time). When one plots those numbers on a graph, a meaningful shape might appear. We identified five shape of change features. Gregory and Shneiderman [24] described three classes for time series analysis but we added two more temporal features for the network analysis.

1) **Growth** or **Contraction** – 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 – such as the number of new members in a NON community. They typically involve counts and statistics.
2) **Convergence** or **Divergence** – A property can grow or contract during its initial stage but gradually becomes stable. For NON we wanted to know if the number of new members per month became stable or not. 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.

4.4.3 Temporal Features of Aggregated Event – Rate of Change

While the previous temporal features were categorical and represent the type of change, other temporal features are needed to quantify the rate of change. Moody et al. [38] called this *relational pace* and defined three different aspects: levels (fast, slow), change (accelerating, decelerating), and stability (cascades, jumps and starts). We kept two here but moved the stability into the previous section i.e. *Shape of Change*.

1) **Speed** – Represents the amount of change in a given time period. For NON analysts were looking for fast growing or slowly dying communities.
2) **Acceleration** or **Deceleration** – Represents the rate of change of speed, e.g. some communities grow faster every month.

5 List of Tasks and Design Space

5.1 List of Tasks

The three dimensions discussed in the previous section (Entity, Property and Temporal Features) help structure the long list of network evolution analysis tasks obtained from the 44 systems (see Appendix A). Three tables complement the list: Table 2 shows the 44 systems, along with the application domain they were mapped to. Table 3 shows the temporal features used in the systems, and Table 4 shows the entity properties they use (Structural Properties and Domain Attributes). The system keys are provided in the leftmost columns for cross-referencing between the tables.

5.2 Design Space

The long list of tasks (Appendix A) is a compact design space representation (Figure 3), which is more practical for designers to use. Design spaces have been used successfully in the past [39], [40], [41] in a variety of situations. For example, in order to construct the taxonomy of input devices (e.g. mice, keyboards, or menus), Card and Mackinlay [39] mapped various input devices into a two dimensional design space using the physical property of the device (delta force, force, movement, or position) and whether it had either a linear or a rotary dimension. Card and Mackinlay could explain the individual nature of the input devices, show relationships among multiple devices, and could suggest what future input devices might get built by examining the empty spots – i.e. where no device existed yet.

The design space of the temporal network visualization tasks (Figure 3) shows two dimensions: (1) Entities by the Granularity of Analysis (X axis) and (2) Temporal Features (Y axis). It should have included three dimensions (as in Figure 4) but after trying multiple possibilities, it was found be too confusing. Therefore, the third dimension (i.e. Structural Properties versus Domain Attributes) was not shown explicitly in the design space. The Structural Properties and the Domain Attributes table (Table 4) is representative and sufficient to guide designers in selecting useful properties or attributes.

5.3 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; (2) identify tasks that are not addressed yet. We can summarize the lessons learned as follows:

Domain attributes prevail – Almost all tasks incorporated domain attributes (Table 4). This is rather a natural observation because hypotheses usually include special domain attributes 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 3 and Figure 3), we can identify the empty spots on the table or the design space (where the example was placed) and get clues about possible

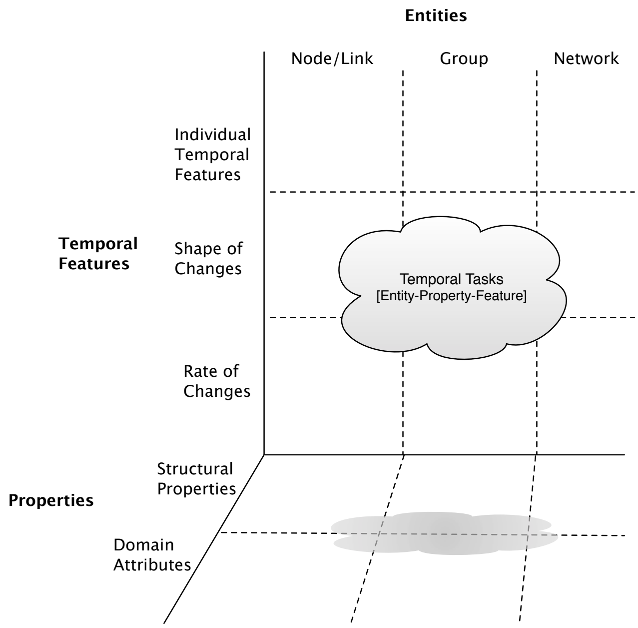

Fig. 4. A design space in 3-dimensions

future additions. The most noticeable empty space is the *Rate of Changes* in the Aggregated Time Event Features column. According to our knowledge, Durant and Truthy were the only researchers that explicitly mentioned the rate of changes (speed) in their data analysis. For non-network time series visualizations, it is not a new topic (e.g. [42]) and the value of this feature for network visualization was already noted by [38]. However, the temporal network visualization systems that were reviewed have not supported this feature much.

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

Multiple granularity of analysis – A lot of systems covered more than one entity. However, 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.

5.4 Compound Tasks

While our design space covers a wide range of tasks, analysts also often combine tasks into compound tasks in order to explore more complex questions. Almost an infinite number of compound tasks can be defined but two dominant cases emerge:

1) **Inferential Compound Tasks** – Analysts can be interested in testing hypotheses between inde-

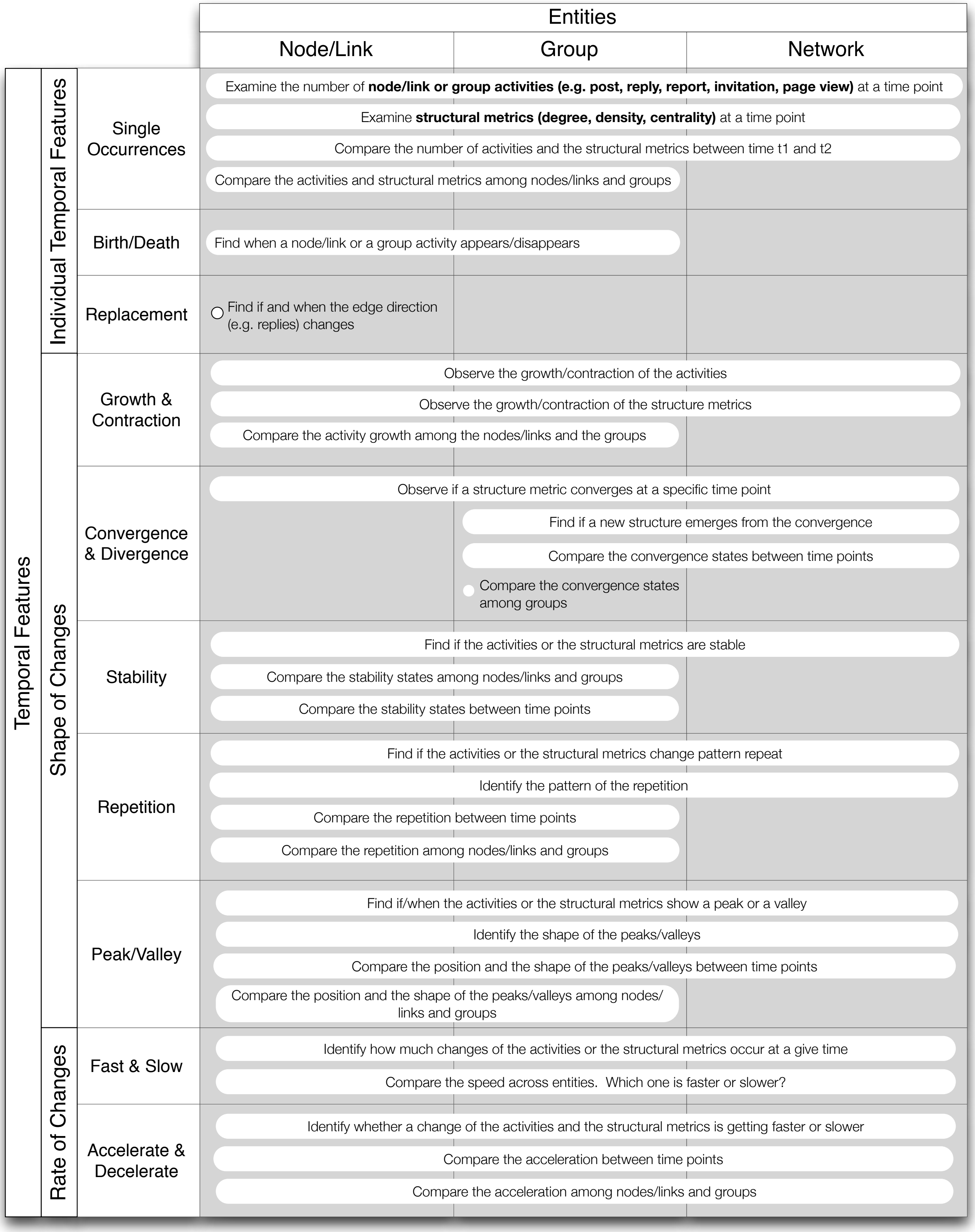

Fig. 3. A design space view of network temporal evolution tasks

pendent (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 are temporal tasks. In our NON example, sociologists tracked the 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.

2) **Comparative Compound Tasks** – Even when no potential cause and effect need to be investigated, analysts might be interested in comparing 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 both cases the tasks might require derived events to be generated and their temporal position compared either visually or statistically. For example, in NON analysts wanted to know if some derived events (such as the peak of activity) preceded, followed or happen at the same time as some other other significant derived events (e.g. the peaks of new users joining the community). While visual inspection was sufficient for our small datasets, creating derived objects that can be manipulated as additional entities in the analysis would facilitate both visual and statistical analysis of larger datasets.

5.5 Low level Data Manipulation Tasks

While others researchers have included data manipulation tasks such as Retrieve Value, Filter, and Compute Derived Value in their analytic tasks (e.g. Amar et al [18]), we excluded them in the design space so as 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 manipulations tasks:

1) **Select and/or aggregate time scale** – This is a basic task used repetitively [43]. 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** – Select a small time range from the entire dataset (e.g. the last month only) or sample discrete time points from the continuous data (e.g. Sundays only).
3) **Align** – Select a reference time point to which the remaining time points will be aligned. Alignment makes the timescale become relative instead of absolute [26].

6 Evaluation with Network Analysis Experts

6.1 Procedure

To test and improve the quality of the taxonomy, we interviewed 9 social network analysis experts conducting research in Sociology, Social Computing, and Social Media. The taxonomy can be used in other domains but social network analysis is currently of interest to many researchers, who seek to answer the following questions:

1) **Comprehensiveness** – Would the experts thought some tasks were missing in the taxonomy?
2) **Ease of Use** – 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 the textual list (Appendix A) and the design space (Figure 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 assessments measures using the 9-point Likert scale

6.2 Results

The 9 experts proposed 40 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.

TABLE 1
Task distribution of experts by temporal feature

	High Match (7–9)	Mid Match (4–6)	Low Match (1–3)
Individual Event Features			
Single Occurrences	33	4	4
Birth/Death	42	1	6
Replacement	23	1	2
Shape of Changes			
Growth/Contraction	43	10	11
Convergence/Divergence	25	8	12
Stability	37	15	5
Repetition	26	9	8
Peak/Valley	25	12	7
Rate of Changes			
Speed	23	16	4
Accelerate	21	5	4
Total	298	81	63

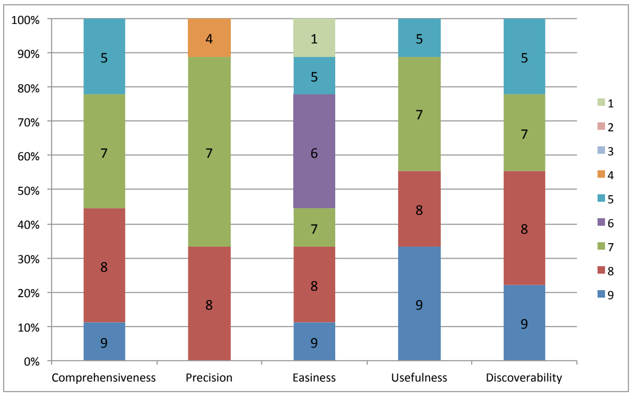

Fig. 5. Subjective feedback on the taxonomy

6.2.1 Analysis of Comprehensiveness

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

1) Inferential analysis between an entity and entity properties – *"I would like to analyze the relationships of the network evolution and the domain attributes 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."*

The two participants who were concerned about these issues gave relatively lower scores (5, where 9 is the high value) (Figure 5, leftmost column). They pointed out that the temporal analyses of network evolution frequently needed to find out complex relationships among *atomic* temporal tasks, such as the inferential or comparative analysis described above. They are not simple sequence of independent tasks. In the initial version taxonomy, we had designed it to best represent all the possible atomic tasks. The *compound tasks* (Section 5.4) in our taxonomy was most similar to the complex tasks the experts mentioned but it only included sequences of atomic tasks and could not reflect the complex nature of the tasks as the experts. Therefore, we went back to our systems and found two main compound tasks: Inferential Analysis and Comparative Analysis, and added them to Section 5.4 as can be seen in the current version.

6.2.2 Analysis of Task Distribution

After confirming the comprehensiveness of the taxonomy, we examined which entities and temporal features the participants were interested in. It is like observing which areas in the design space (Section 5.2) were picked up more frequently. A similar trend could be observed from the systems used for constructing the taxonomy (Table 3) but this process also showed the experts' potential tasks.

Table 1 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 5. 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.

6.2.3 Analysis of Subjective Feedback

Figure 5 shows the subjective feedback from the participants on five aspects of the taxonomy. As discussed in Section 6.2.1, the majority of them (78%) agreed on the comprehensiveness (score 7–9). The remaining 22% gave 5 out of 9 but they were all concerned about the compound task issue, rather than suggesting new temporal features.

Most of them (more than 75%) rated positively (score 7–9) on the *Precision*, *Usefulness*, and *Discoverability*. They were neutral on the *Ease of Use*. More than 40% still rated positively (7–9) but around 40% of them gave mid-range scores. One participant 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 make clear the meanings and highlight the differences.

7 Conclusions and Future Work

This paper proposes a task taxonomy for visual analysis of network evolution. We structure the definition of the tasks using three dimensions – Network Entity, Property, and Temporal Features – and identify the elements of each dimension. This task taxonomy, based on 44 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 attributes, (2) temporal features less explored, (3) higher propensity to implement the simpler individual temporal features, and (4) the potential of methods for integrating different granularity of analysis into a single framework.

After building the taxonomy, we tested it by interviewing 9 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 attributes into the TempoVis [32] 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 well-integrated user interfaces.

APPENDIX A TASK TAXONOMY

A.1 Individual Temporal Event Tasks

A.1.1 Single occurrences

[s1] Examine a specific value of an entity of one or more discrete time point(s).

[s2] Compare the value of entities of multiple time points.

[s3] Compare the value of entities among entities.

[s4] Compare multiple time points using similarity measures.

- Observe which and when high centrality nodes appear (Flemming).
- Observe the change of network structure on a specific date by overlaying the two cliques on a single node-link diagram (GeoTemporalNet).
- Compare two sub-groups of callers (who were assumed to have switched their cellphones) using structural equivalence measures (GeoTemporalNet, SocialDynamicsVis).
- Compare multiple network diagram snapshots extracted from different time points by examining the change of edge weights of interest (SocialAction).
- Identify a high concentration of cellphone calls on a specific date (SocialDynamicsVis).

A.1.2 Birth and Death

[bd1] Find if and when a specific entity appears and disappears.

[bd2] Find an emergence of a new network structure such as an interaction pattern, or sub-groups.

- Identify when co-authorship ties between multiple nodes appear (Flemming).
- Browse and find when and how often does a specific type of forum participants appear (Durant).
- Find when a group of callers disappear (by the call frequencies) and when another group of callers appear (SocialDynamicsVis).
- Observe if an existing sub-group (dis)appears on a specific date (Prajna, PieSpy).
- Observe the network structure change and find if there is any new emerging sub-groups (SoNIA-1, SoNIA-2).
- Observe the network structure change and find if there appears a new communication pattern (SoNIA-3).
- Identify the birth of the communication groups (iQuest, TeCFlow, Arikan, Truthy).
- Identify the birth of the race groups (Morris).
- Identify the birth of virtual communities (Commetrix).

A.1.3 Replacement

[rp1] Find the change of entity properties.

- Discover the switch of cellphone ID's occurred on the same day (Prajna).
- Find the switch of edge directions according to change of the communication pattern (SoNIA-3).
- Observe which people become obese – replacement of a person's property from normal to obese (Obesity)
- Identify the topic switches in individual nodes or in groups (Thiel).

A.2 Aggregated Temporal Event Tasks

A.2.1 Growth and Contraction

[gc1] Observe the value of an entity measure as it increases or decreases.

[gc2] Compare the growth or the contraction of an entity between time points.

[gc3] Compare the growth or the contraction pattern among entities.

- Observe the growth of the overall network (Durant, PieSpy, Burch, Arikan2005, Arikan2007, Collins, Krebs).
- Observe the growth of the co-author groups (C-Group).
- Observe the growth of the communication groups (iQuest, TeCFlow, Arikan, Truthy).
- Observe the growth of the racial groups (Morris).
- Observe if the transitivity of the global network grows or contracts (SoNIA-1, SoNIA-2).

- Observe if the reciprocity of the global network grows or contracts (SoNIA-1, SoNIA-2).
- Observe the growth and contraction of cell phone call frequency. (SocialAction).
- Identify the growth of virtual communities (Commetrix).

A.2.2 Convergence and Divergence

[cd1] Observe the value of an entity measure and find if and when it converges to a specific point.
[cd2] In case of convergence, find if a new structure appears at the point.
[cd3] Compare the convergence states.

- Find if the transitivity converges and stabilizes after growing to a specific time point (SoNIA-1, SoNIA-2).
- Find the convergence point of the transitivity and observe if the resultant network emerges (SoNIA-1, SoNIA-2).
- Compare the result of the emerging network with social balance theory. That is, whether the process of making friends is achieved through already close friends (SoNIA-1).
- Find if there is any difference between the global network and its sub-groups in terms of the convergence metric (SoNIA-2).
- Find the emergence of a specific stage in evolution simulation (Morphology).
- Find the emergence of coherent interacting structures in Cellular Automata (Wuensche).
- Find the emergence of direct human contact patterns (SocioPatterns).

A.2.3 Stability

[st1] Find if a changing value of an entity stabilizes.
[st2] Identify when the stabilization happens.
[st3] Compare the stability states.

- Observe if the collaboration pattern is growing or stabilized and compare them by international region (TimeMatrix).

A.2.4 Repetition

[re1] Find out if a pattern of an entity value change repeats.
[re2] Identify the repeating pattern.
[re3] Compare the repetition patterns.

- Observe the value of the network reciprocity measure fluctuates (SoNIA-2).
- Observe the repeated communications between a teacher and his students (SoNIA-3).
- Compare the two different communication patterns of two classrooms, one of which is more obedient and the other is not (SoNIA-3).

A.2.5 Peaks or Valleys

[pv1] Find out if there are any peaks or valleys of an entity value change over time.
[pv2] Identify the shape of the peaks/valleys. Do they change sharply or slowly?
[pv3] Compare the peak/valley patterns.

- Identify a sudden peak within a time range and observe whether their duration is short or long. Compare them with structural properties or domain attributes such as topic (Shamma, Lichtenberg).
- Find any number of collaboration of the players peaked. If any, when was it (TimeMatrix)?

A.3 Rate of Changes

A.3.1 Fast or Slow

[fs1] Identify how many changes an entity had during a given time period.
[fs2] Compare the difference of changes of multiple entities. Find out which one is faster or slower.

- Compare the speed of growth of nodes by different attribute types (Durant).
- Compare the speed of infection spreadings between multiple groups (Morris).

A.3.2 Accelerating or Decelerating

[ad1] Identify whether a change is getting faster or slower.
[ad2] Compare the acceleration or deceleration patterns between entities.

Acknowledgments

We appreciate the support of National Science Foundation grant IIS0968521, Supporting a Nation of Neighbors with Community Analysis Visualization Environments, plus National Science Foundation-Computing Research Association Computing Innovation Fellow, Postdoctoral Research Grant for Jae-wook Ahn. We also appreciate the efforts the participants who evaluated the taxonomy and provided valuable feedback.

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TABLE 2
Temporal network visualization systems

Keys	Authors	System/Study Name	Application Domain
Research Publications (17)			
C-Group	Kang [44]	C-Group	citation network
Commetrix	Trier [45]	Commetrix	Community network
Durant	Durant [46]	-	discussion board
Fleming	Fleming [47]	-	Patent co-authorship network
iQuest	Gloor [48]	iQuest	communication archive (e-mail, phone records, blogs, etc)
Morris	Morris [49]	-	Health – HIV transmission
Obesity	Christakis and Fowler [50]	-	Health (obesity)
PieSpy	Mutton [51]	PieSpy	IRC communication
Powell	Powell [52]	-	affiliation network of life science institutions
Shamma	Shamma [53], [54]	-	microblog communication
SoNIA-1	Moody [38]	SoNIA	social network – social balance
SoNIA-2	Moody [38]	SoNIA	social network – Newcombs fraternity
SoNIA-3	Moody [38]	SoNIA	social network – education
TeCFlow	Gloor [55]	TecFlow	email archive
Thiel	Thiel [56]	-	Scientific concept shift
TimeMatrix	TimeMatrix [28]	TimeMatrix	inter-organizational collaboration network
Zhang	Zhang [57]	-	invitation network
Competition Systems (5)			
GeoTemporalNet	Ye [58]	GeoTemporalNet	VAST08 cellphone network mini-challenge [31]
MobiVis	Correa [59]	MobiVis	VAST08 cellphone network mini-challenge
Prajna	Swing [60]	Prajna	VAST08 cellphone network mini-challenge
SocialAction	Perer [61]	SocialAction	VAST08 cellphone network mini-challenge
SocialDynamicsVis	Farrugia [62]	SocialDynamicsVis	VAST08 cellphone network mini-challenge
Online materials (22)			
Arikan	Arikan [63]	-	Twitter network
Arikan2005	Arikan [64]	-	Fashion network
Arikan2007	Arikan [65]	Transaction Graph	Transaction network
Backchannel	Stamen Design [66]	Backchannel	Social network
Burch	Burch [67]	-	Internet
Collins	Collins [68]	-	Last.fm label network
Email Map	Baker [69]	Email Map	E-mail archive
Geneffects	Geneffects [70]	-	Genetic algorithm visualization
Hwang	Hwang [71]	-	Subway network
Koblin	Koblin [72]	New York Talk Exchange	Phone network
Krebs	Krebs [73]	-	Business network
Lichtenberg	Lichtenberg [74]	-	Biology network
Marsh	Kolata [75]	-	Enron e-mail exchange
Morphology	Chang [76]	Morphology	Biology network
Poetry Machine	Link [77]	Poetry Machine	Semantic network
Poke London	Poke London [78]	-	Digital creativity network
Posavec	Posavec [79]	-	Knowledge (word) network
SocioPatterns	Broek [80]	SocioPatterns	Social network
time=net.work	Lamanna [81]	time=net.work	Transportation network
Truthy	Indiana University [82]	Truthy	Twitter network
Twitter Lyrics	Smits [83]	Twitter Lyrics	Twitter referring music titles
Wuensche	Wuensche [84]	-	Biology network

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TABLE 3
Temporal network visualization systems – organized by the temporal analysis features

•: node/link, ⊗:subgroup, ◯:network

Keys	Temporal Analysis Features									
				Aggregated Time Event Features						
	Individual Time Event Features			Shape of Changes					Rate of Changes	
	Single Occurrences	Birth/ Death	Replacement	Growth Contraction	Convergence Divergence	Stability	Repetition	Peak Valley	Speed	Accelerate
Arikan		⊗		⊗						
Arikan2005				•◯						
Arikan2007	•	•		◯						
Backchannel	•	•								
Burch				◯						
C-Group		⊗		⊗						
Collins	•	•		◯						
Commetrix		⊗	⊗	⊗						
Durant	•	•		◯					•	
Email Map	•	⊗		⊗						
Flemming	•	•								
Geneffects	•									
GeoTemporalNet	•⊗		•⊗							
Hwang				•						
iQuest		⊗		⊗						
Koblin				•						
Krebs			•	◯						
Lichtenberg	•							•		
Marsh			•							
MobiVis	•⊗		⊗							
Morphology	•	•	•		◯					
Morris		⊗		⊗					⊗	
Obesity			•							
PieSpy	•	⊗		◯						
Poetry Machine	•	•								
Poke London	•	•								
Posavec	•	•								
Powell	⊗◯	•		◯						
Prajna	◯	•	•							
Shamma								◯		
SocialAction	•		•	◯						
SocialDynamicVis	•⊗	•	⊗							
SocioPatterns	•	•			◯					
SoNIA-1	•	⊗		◯	◯					
SoNIA-2	•	⊗		◯	◯					
SoNIA-3	•	◯			◯		◯			
TecFlow		⊗		⊗						
Thiel			•							
time=net.work				•						
TimeMatrix	⊗			◯		◯		•		
Truthy		•⊗		⊗						
Twitter Lyrics	•	•								
Wuensche					◯					
Zhang				•⊗						

TABLE 4
Temporal network visualization systems – organized by the structural properties and the domain attributes

•: node/link, ⊗:subgroup, ◯:network

Keys	Entity Properties			
	Structural Properties		Domain Attributes	
Arikan	•⊗	Centrality, Group membership		
Arikan2005	•◯	Density, Network size		
Arikan2007	•◯	Edge connectedness, Network size		
Backchannel	•	Edge connectedness		
Burch	◯	Network size	◯	Internet size growth
C-Group	•	Edge direction of the focal-pairs, Group membership	⊗	Author group
Collins	•	Degree, edge connectedness	•	Music label
Commetric	•⊗	Edge connectedness, Group membership		
Durant	•	Edge direction	•	Node type: provider, consumer, facilitator
Email Map	⊗	Group membership		
Flemming			•	Patent organization and importance
Geneffects	•	Edge connectedness	•	Genetic algorithm tree
GeoTemporalNet	•⊗◯	Degree, Edge direction/weight, Network layout	•	Call frequency, Geo-location, Cellphone ID
Hwang	•	Edge weight	•	Subway Traffic
iQuest	⊗	Betweenness-centrality	⊗	Betweenness-centrality
Koblin			•	Number of talks in a telephone network
Krebs	◯	Network size	•	Role in business network
Lichtenberg	•	Degree	•	Protein interaction
Marsh			•	E-mail address
MobiVis	•⊗◯	Degree, Edge direction/weight, Network layout	•	Call frequency, Geo-location, Cellphone ID
Morphology			◯	Evolution simulation
Morris	⊗	Group membership	•	Sexual partnership, HIV infection
Obesity	•	Edge connectedness between obese and non-obese people	•	Obesity
PieSpy	•	Centrality		
Poetry Machine	•	Edge connectedness	•	Emergence of meaning
Posavec	•	Edge connectedness		
Powell	⊗◯	Cohesion, Homophily		
Prajna	•⊗◯	Degree, Edge direction/weight, Network layout	•	Call frequency, Geo-location, Cellphone ID
Shamma	•	Centrality	•	Topic
Poke London	•	Edge connectedness	•	Institutional relationships
Social Action	•⊗◯	Degree, Edge direction/weight, Network layout	•	Call frequency, Geo-location, Cellphone ID
SocialDynamicVis	•⊗◯	Degree, Edge direction/weight, Network layout	•	Call frequency, Geo-location, Cellphone ID
SocioPatterns	•	Edge connectedness	◯	Human contact pattern
SoNIA	•◯	Edge direction/weight, Transitivity, Reciprocity	◯	Class type: obedient, rebellious
TecFlow	⊗	Betweenness centrality, Core/periphery structure	⊗	Innovation networks
Thiel	•	Group membership	•	Scientific concepts
time=net.work	•	Betweenness-centrality		
TimeMatrix	•	Density, Centrality	⊗◯	Inter-organizational collaboration
Truthy	•⊗	Edge connectedness, Group membership		
Twitter Lyrics	•	Edge connectedness	•	Album – twitter relationships
Wuensche			◯	Coherent interaction structure in cellular network
Zhang	•	Degree, Hub	•	Organizational position, Acceptance rate