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DMNEVis: A Novel Visual Approach to Explore Evolution of Dynamic Multivariate Network

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***Abstract*— The multivariate network consists of a series of nodes and links with multiple attributes. The topology and multivariate information of network will change over time, namely with dynamic change. Many real-world physical and non-physical phenomena can be modeled as such networks, such as population migration, proteins interactions, transactions, etc. It is of great application value for different domains if users can effectively mine the potential information in the process of networks evolution. However, existing visual analytics systems of multivariate network focus on group network or ego-centric network respectively, and fail to analyze the evolution of both them. To solve this problem, we propose DMNEVis (Dynamic Multivariate Network Evolution Visualization), a visual analytics system that helps explore the evolution of the dynamic multivariate network from group network to ego-centric network step by step. The system provides a series of novel visual tools for users to understand evolution from both group and individual level. Finally, we demonstrate effectiveness of DMNEVis through a case study on the co-authorship dataset.**

Keywords*— *dynamic multivariate network, network evolution, group network, ego-centric network, visual analytics

I. Introduction

Many phenomena in real world, including physical and non-physical phenomena, can be modeled as a network in which the entities are the nodes and the relations are the links, such as financial transactions, migration, social networks, academic collaboration, company mail system, etc. Network data analysis has been studied in different domains, for example, in the medical domain [1], analyzing the correlation between the patients' social interactions and their health status is proved to be useful to assist in treatment; in bioinformatics [2], analysis of protein interaction networks are help to discover protein functions; in commercial companies [3], by analyzing the communication among employees and capturing abnormal entities, it helps prevent the occurrence of information security accidents. In addition to the network structure information composed of nodes and links, these networks often contain more complex multivariable information, changing during the evolution of the network.

Traditional data analysis methods are often based on priori models focusing on the specific detectable and predictable task, but they are not able to explore and discover the unknown patterns. At the same time, due to the complexity of data, it is impossible to fully rely on automatic methods to deal with some situations well. Although many visual analytics methods have been applied to the evolution of network, existing methods can not well meet the following requirements of exploring dynamic multivariate network:

- Show and analyze the evolution of the topological structure and attributes of dynamic multivariate network over time.
- Provide an exploration process from global level to individual level.

In this paper, we introduce DMNEVis, an interactive visual analytics system to explore the evolution of dynamic multivariate network. Using a novel and flexible design, DMNEVis addresses the requirements listed above. DMNEVis supports the exploration for both group network and ego-centric network, provides different perspectives and scales for users to effectively explore the evolution of dynamic multivariate networks. Ego-centric network consists of an ego and the nodes and links associated with the ego. However, group network do not have the central node, i.e., they contain multiple central nodes. Hence, we can draw a conclusion that ego-centric network is a part of group network, and the relationship between them is local and global. In summary, this paper has following contributions:

- An interactive visual analytics system to explore the evolution of the dynamic multivariate network from group network to ego-centric network stage by stage.
- A network visualization method based on group division and progressive levels for group network, and a vertically stacked adjustable network visualization method for ego-centric network.
- A case study using DBLP (a well-known computer literature retrieval service website) co-authorship data to verify the effectiveness of DMNEVis.

The remainder of this paper is organized as follows. In Section II, we will discuss the related work. In Section III, the design goals will be described. In Section IV, our design ideas and implementation will be introduced. In Section V, we will

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give a case study to demonstrate the novel approach. Finally, the conclusions and future work will be discussed in Section VI.

II. Related Work

At present, many researchers have paid attention to the evolution of dynamic multivariate network using visualization. We will discuss them from two perspectives: analysis techniques and analytics systems.

Animation-based and timeline-based are two mainstream techniques for exploring the evolution in dynamic multivariate network. Eades et al. [4] firstly proposed the method of animated transition to explore changes in graph structure over time. Although the method of animation has commendable visual effects, there are still many problems: 1) it brings great users' visual burden. At adjacent moments, users can often capture the differences between them, but for more distant time comparisons, they need to be repeatedly rolled back or forward through timing navigation; 2) in order to ensure the stability of topological structure and maintain the mental map in users' memory, the layout needs to meet quiet high requirements; 3) it is difficult for animation-based method to add interactive views. Different from animation-based method, in timeline-based method, the network is mainly represented by the node-link diagram [5]. The network snapshot is often placed in the form of juxtaposition [6], stacking [7], [8], or integration [9], [10]. This method can simultaneously display the information of multivariate network at multiple moments and analyze the evolution of dynamic network in the form of static graph. In order to make full use of space and be able to track changes in nodes, many visualization methods [6], [11] lay out the nodes on y-axis, and utilize x-axis representing time. The nodes will be connected by curves or straight lines thereby tracking the evolution of nodes at different moments and the relationship between nodes at the same time. This method is more limited by space and network size, but it is advantageous for exploring ego-centric network (smaller networks). There are also some visualization methods that incorporate animation-based and timeline-based methods [12], [13]. More about these methods are available in [14].

Recently, in addition to animation-based, timeline-based, and hybrid methods, researchers have proposed new methods to show evolution of multivariate network. Elzen et al. [15] conducted dimensionality reduction from the snapshot of network structure to a point, and the points (network snapshots) at neighboring moments are connected by lines. The time is mapped to the color of the node, thereby exploring the changes of network state in limited space, such as the transition between three states: stability, circulation and abnormalities. However, this method is only applicable to specific network data (discovering a specific network state requires at least more than 20 time steps), and is more suitable for the exploration of macro information.

For the perspective of visual analytics, most of the existing systems for exploring the evolution of networks are directed to a single group network [16], [17] or ego-centric network [10], [18–21]. Group network contains multiple egos, and the number of node is often larger than ego-centric network. Due to differences in research objects, the analysis methods and tasks of these two types of networks are different. For example, Elzen et al. [16] perform time series navigation using the statistical information view, to display and analyze the overall communication status between communication base stations at different moments, but only one snapshot can be displayed at each moment. Shi et al. [10] proposed a 1.5D visualization method for ego-centric network, which maps time to one dimension in two-dimensional space and distributes nodes associated with egos to both sides of the timeline according to time, but the locations of these nodes are not strictly related to the corresponding time. This method can simultaneously display the nodes and links of network in all time-slices by the form of static graphs, and focus on egos to explore the evolution of the relationship between this ego and alters. Due to the global and local relationship between group network and ego-centric network, the global evolution rules are often difficult to accurately reflect the local situation, and vice versa.

In general, although the visualization methods of network evolution has matured, the existing visual analytics systems for network evolution are oriented to single group network or ego-centric network, lacking joint analysis of these two types of networks. Compared with them, DMNEVis provides a visual analytics model that simultaneously analyzes evolution of group network and ego-centric network, and helps analysts to gain insights more comprehensively by a series of visual analytics methods.

III. Design Goals

In this study, DMNEVis is designed to explore evolution of the dynamic multivariate network, including group network and ego-centric network. At the same time, the analysis of these two kinds of networks will help users to grasp the global and local information, so as to understand the data more comprehensively and accurately.

After referring to other literature related to the above, our specific list of design goals is as follows:

1) ***For group network****:* We pay attention to the evolution of the network as a whole, including the topology and the evolution of the dynamic multivariate network.

- **Explore the evolution of network topology, global attribute and node behavior over time**. Users should be able to find out the form and the change of network topology over time. Using DMNEVis, the changes of parameters such as aggregation coefficient, average centrality, network size, properties of specific domain can be observed. And mainstream node behavior patterns can be detected.
- **Explore the change of community distribution in group network**. Users should be able to spot new communities and disappeared communities at concrete time point, and observe mergers or splits in multiple communities.

2) ***For ego-centric network****:* We pay attention to the evolution of nodes and links.

- **Explore the life cycle of nodes and links**. Users should be able to come to realize when a node first appears, disappears at what time, and reappears after disappearing for some time.

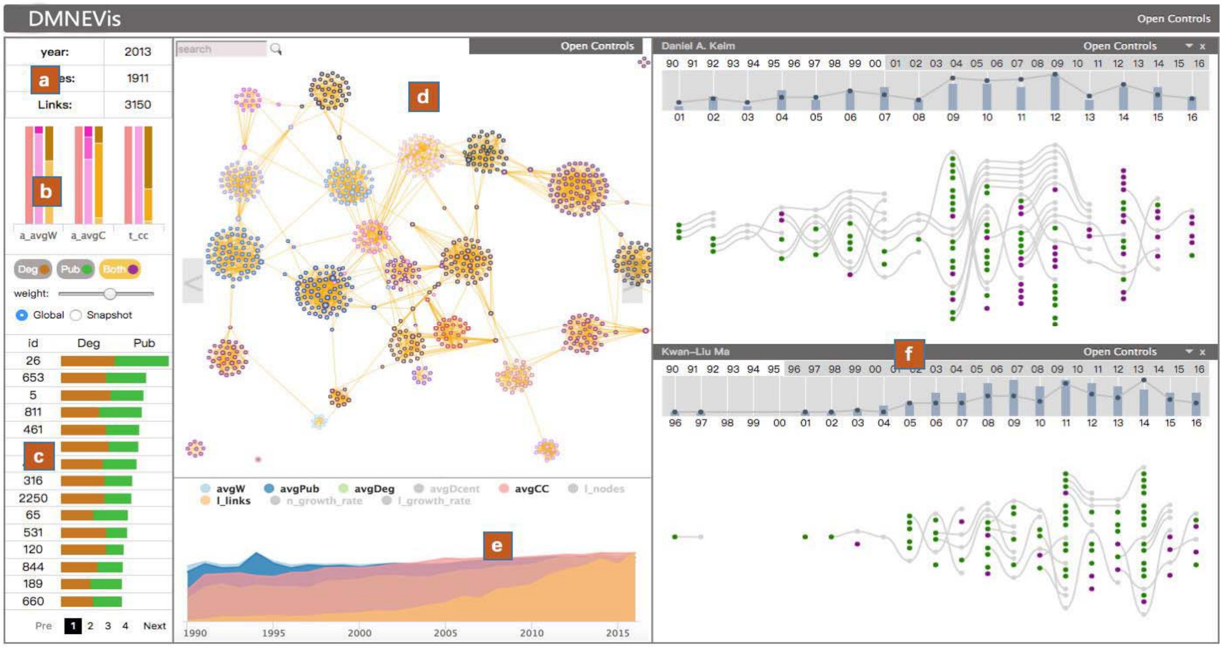


Fig. 1. An overview of DMNEVis on a dataset about co-authorship. (a) the *Data Attributes Module* shows time, nodes and links; (b) the *Attribute Distribution Contrast View* shows distribution of multiple attributes of the selected group; (c) the *Weighted Attribute Sorting View* allows users to find some nodes interested by filtering; (d) the *Group Network View* shows the topology and the evolution of the whole dynamic multivariate network; (e) the *Attribute Evolution View* allows *u*sers to observe the evolution of multiple attributes; (f) the *Ego-centric Network View* shows the evolution of ego-centric network of the node selected by the user. It also supports the comparison of multiple ego-centric networks.

- **Explore the evolution of attributes of nodes and links**. Users should be able to intuitively perceive the enhancement and attenuation of attributes and find out the state of volatility.

*3) **For the evolution of global to local**: It is* mainly related analysis and comparative analysis.

- **Analyze the differences between the same attributes or behaviors of different nodes at some time, and the evolution of patterns over time**. From group network to ego-centric network, system should allow users to find the association strength between different nodes at some point of time and the center node. And users can find changes in the association strength with the passage of time.

- **Analyze the influence of some node behaviors on the group and the correlation between multiple attributes**. In group network, the nodes associate with a node can be observed, thus finding out whether these nodes have an influence on each other in ego-centric network.

IV. System Overview

We propose web-based visual analytics system named DMNEVis to provide interactive exploration of the dynamic multivariate network. Resort to DMNEVis, the details of many previously invisible dynamic multivariate network and the evolution from group network to ego-centric network can be discovered.

As shown in Fig. 1(a), DMNEVis allow users select the time they are interested in and help they know the number of nodes and links in the network. The *Attribute Distribution Contrast View* (Fig. 1(b)), the *Weighted Attribute Sorting View* (Fig. 1(c)), and the *Attribute Evolution View* (Fig. 1(e)) can be obtained in the *Auxiliary View*. The *Group Network View* is placed at Fig. 1(d), and the *Ego-centric Network View* is placed at Fig. 1(f).

In order to explain the workflow of DMNEVis, we will deconstruct it by demonstrating the design and function of each view in the following sections.

A. The Group Network View

The existing visualization methods for the topology of group network, especially for large-scale networks, mostly adopt hierarchical design. But there are two notable problems. One is the topology characteristics shown in the layout results are not obvious, and another is lack of explicit representation of whether or not to display information. The *Group Network View* improves the traditional force-directed layout algorithm to highlight topological structure features and bridge nodes. It resolves the limitations of slow rendering speed and limited space through the hierarchical design, and adds a shadow effect to indicate if there is any undisplayed information (Fig. 2(a)(b)(c)).

Fig. 2 presents the detail of the view. Based on the traditional force-directed layout algorithm, the force source of the node is redesigned. The nodes in the same group are closely grouped together to be displayed in a disc shape, highlighting the group structure and increasing symmetry. The bridge node is wrapped in black border, which can be as far as possible distributed

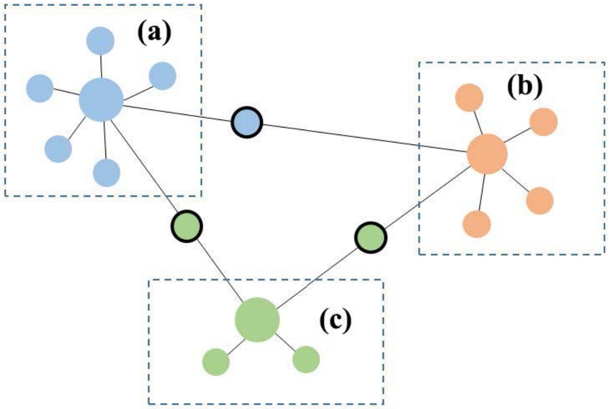
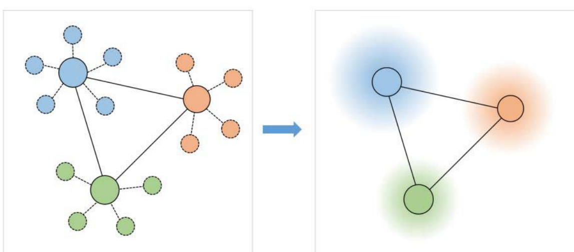


Fig. 2. The group network based on topology layout.

among the groups to help users better grasp the topology of the whole network.

For the purpose of reducing the rendering time and the visual confusion of the limited space after increasing the number of nodes, we use a hierarchical approach to look at the details of the network and display explicitly undisplayed information by shadow (Fig. 3(b)). The view only shows nodes of a particular level. Different colors correspond to different groups, with the centrality as the importance evaluation criteria for nodes. When zoom out, lower level of nodes and links will be replaced by shadows, it depends on the size of the nodes in the group. In addition, transparency is closely related to the number of nodes not shown in the group.



(a) (b)

Fig. 3. The group network with zooming and shadow design.

Zooming and panning are the main interaction for this view, and the search and lock node functions are added to compare ego-centric networks' evolution.

B. *The Ego-centric Network View*

When users find the node of interest in the *Group Network View* or in the *Auxiliary View*, they can click it to jump to the *Ego-centric Network View* to further analyze the network centered on the ego. It focuses on a small network centered on an ego. Unlike the *Group Network View*, which only displays a snapshot of the network at a time, this method displays the network state at all time or a period of time to help users better understand the evolutionary information of the network over the entire time span.

In this design, the same node may not be on a straight line at different times, followed by a curve connection, making full use of the longitudinal space. To meet users' analysis requirements, the view provides two layout methods based on topology and attributes respectively. The relationship between nodes in a network snapshot are not represented by explicit links, but by providing the interaction of focus and context combinations to view the associations and reduce confusion. The view allows users to switch between the *Detail View* and the *Community View*, helping users analyze a network from different levels.

The *Ego-centric Network View* consists of an *Ego Attribute Evolution Module* and a *Network Evolution Module*.

1) The Ego Attribute Evolution Module: This module shows the evolution of the attributes of the selected ego, which can simultaneously show the changes of the two attributes. It mainly uses line graph and histogram to distinguish. Through control panel, we can switch display attributes. At the same time, the module provides a global timeline and a local timeline to filter time. By selecting a period of time on the global timeline, the local timeline will automatically adapts to this time period, thereby changing the display. The *Network Evolution Module* will change with the local timeline and increase the gap between the left and right time-slices. As shown in Fig. 4(a), the whole time span is 1990-2016, and the current selection is from 2004 to 2016.

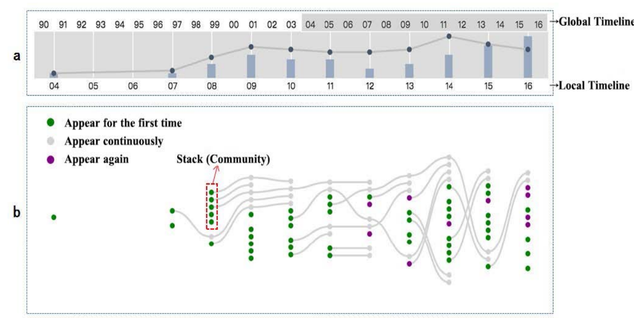


Fig. 4. The *Ego-centric Network View* supports controlling the timeline and adds color coding to track nodes.

2) The Network Evolution Module: This module has two main view representations, including the *Detail View* and the *Community View*.

a) The Detail View: The view shows the nodes directly associated with the selected ego. The nodes on the vertical axis represent the data that is associated with the ego at the current moment and is represented by a circle. As shown in Fig. 4(b), the nodes are connected by the curve so that the nodes can be tracked (for solving individual level tasks). Moreover, the view uses green, gray, and purple to indicate whether nodes appear for the first time, appear continuously, or reappear. The view provides two types of nodes layout on the vertical axis, including the method based on network topology and attribute. The layout method is helpful to explore the change of network topology. The first method is helpful to explore the change of network topology (Fig. 4(b)). The second method is helpful to explore the evolution of multivariate information (e.g. the changes of attributes distribution).

b) The Community View: As shown in Fig. 5, different from the *Detail View*, each rectangle in the *Community View* represents a community representing a stack in the *Detail View*.

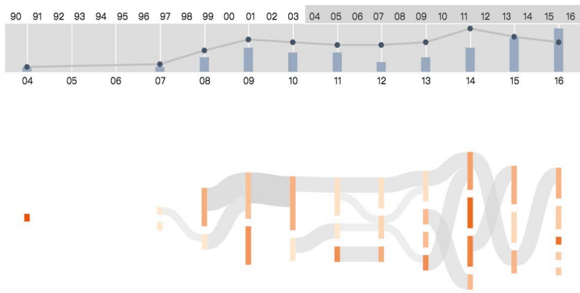


Fig. 5. *The Community View.*

The height of the rectangle indicates the number of individuals in the community. The direction of the individual in the community is shown in the form of flow, and we call the flow of the left and right sides of the rectangle as "inflow stream" and "outflow stream". The amount of inflow and outflow is represented by dual coding: the thickness and transparency of the flow. Simultaneously, in order to explore the difference between community attributes, the average value of individual attributes in the community (only the numeric attribute) is mapped to the rectangle color.

In addition, in the cause of comparing and analyzing different ego-centric networks, the view allows users to observe multiple ego-centric networks at the same time (Fig. 1(f)). Avoiding duplicate rendering and maintain the user's operation record, the view provides the folding operation, which can leave the space for displaying more ego-centric networks.

C. The Auxiliary View

1) The Weighted Attribute Sorting View: This view (Fig. 1(c)) is similar to table display mode. It represents the numbers as filled rectangles. The length of each rectangle corresponds to the size of the attribute value. The color is used to distinguish different attributes, corresponding to the top label. The *Weighted Attribute Sorting View* supports single attribute sorting and double attributes sorting. When double attributes sorting is performed, users can set each attribute weight by dragging and dropping the slider, and then display it in a stacked form in the table. Besides, the view provides both global and snapshot modes, showing different data objects respectively. The former displays the data object in all time, the latter shows the data object under the current selected time.

2) The Attribute Distribution Contrast View: This view is mainly used to show the distribution of multiple attributes (only for numeric attributes) of selected group in group network and to compare and analyze them. Users can observe the details from a multi-column histogram chart (Fig. 1(b)).

3) The Attribute Evolution View: This view (Fig. 1(e)) uses the flow diagram to show the evolution of topology and domain attributes over time in group network, and uses colors to distinguish different attributes and set transparency for each color. To a certain extent, the effect of the flow coverage is reduced so that the correlation analysis between the two attributes can be carried out. Each attribute has a different scale, which can be used to view attribute values of different attributes at different time-slices through hovering. At the same time, user can select whether to display the attribute by clicking on the tab at the top, and when users find the time span of interest, the snapshot in the *Group Network View* can be switched by clicking on the timeline.

V. Case Study

This section aims at demonstrating the usefulness of DMNEVis using co-authorship data from DBLP. We select papers published in the following journals or conferences (TABLE I) from 1990 to 2016, totaling 23344.

TABLE I. Journals And Conferences List.

Type	**Name**
Journal	IEEE Transactions on Visualization and Computer Graphics (TVCG)
Journal	Computer Graphics Forum (CGF)
Journal	Journal of Visualization (JoV)
Journal	Information Visualization
Conference	ACM Conference on Human Factors in Computing Systems (CHI)
Conference	IEEE Visualization Conference (VIS)
Conference	IEEE Pacific Visualization Symposium (PacificVis)
Conference	The Eurographics Conference on Visualization (EuroVis)

After extracting authors and relations, the node and link attributes we use are as follows:

*1) **The Node Attributes**:*

- **a_pub**: The annual number of papers published by the author.
- **t_pub**: The total number of papers published by the author.
- **a_type**: The type of annual papers published by the author (journal, conference, both).
- **a_degree**: The annual number of collaborators in the year.
- **t_degree**: The total number of collaborators.
- **a_avgC**: The average centrality of all collaborators of the author in the year.
- **a_cc**: The local aggregation coefficient of ego-centric network centered on the author in the year.
- **a_avgW**: The average intensity of cooperation between the author and collaborators in the year.

*2) **The Link Attributes**:*

- **weight**: The number of cooperation between the two authors in the year.
- **type**: The type of papers published by the two authors (journal, conference, both).

Concretely, We will complete this case study from group network to ego-centric network bit by bit. The *Attribute Evolution View* is the entry point.

the view). After zooming in, it can be observed that cooperation among these large groups begins to emerge, thus forming a large academic circle. With the help of the A*ttribute Distribution Contrast View*, we also find that researchers are increasingly willing to publish papers cooperatively, and that the relationships within the team are becoming more and more closely linked.

After selecting Hans-Peter Seidel who has published papers most from the *Weighted Attribute Sorting View*, let's focus on Fig. 8. Prof. Seidel's *Ego Attribute Evolution Module* shows that he published papers in related fields for the first time in 1991, no papers in 1992-1993. Then he published papers for 23 consecutive years from 1994 to 2016, and the number of publications shows an increase in two periods from 2002-2008 to 2010-2014. The trend, after 2014, presents a more obvious downward. In addition to the number of collaborators from 2008 to 2010, the number of collaborators is generally in a relatively uniform trend. In order to observe Seidel's role in the network from the perspective of topology structure, we switch to the *Group Network View*. By highlighting (Fig. 9), Seidel is found to have the highest node degree in his group (the largest radius), indicating that he has always maintained a more central role in the team.

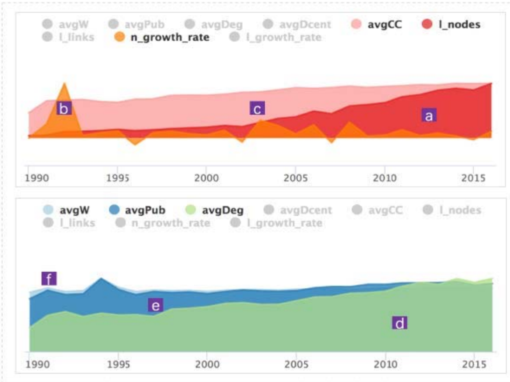


Fig. 6. The *Attribute Evolution View* of the group network.

Firstly, we select node number, node growth rate and global aggregation coefficient as display attributes. Through the changes in the number of nodes (Fig. 6(a)) and the growth rate of nodes (Fig. 6(b)) in the view, it can be seen that the number of nodes at a certain moment has decreased, and the overall situation has shown an upward trend, and the upward momentum has not shown signs of slowing down. From the perspective, it can be inferred that visualization is a new field and is currently in a rapid development period. At the same time, the network aggregation coefficient (Fig. 6(c)) presents a slower growth rate.

Then, we switch attributes to average weight of cooperation (Fig. 6(f)), average number of publications (Fig. 6(e)), and average number of collaborators (Fig. 6(d)). From the figure, the publications of researchers has maintained a slow growth trend every year. On the one hand, it shows that the individual's academic ability is gradually increasing. On the other hand, it also reflects that there are still many issues worth researching in this field. The average weight of cooperation shows a more stable situation. It can be inferred that the current cooperation of researchers is not limited to a fixed number of people, but is constantly expanding the scope of cooperation.

After a preliminary understanding of the evolution of relevant properties of the whole network, we further explore the topology structure. We select 1991-1993 and 2011-2013, observing their respective topological performance. Fig. 7 shows that there were some relatively independent small teams (discrete shadow points) in the early days. There are fewer connections between them, and the entire network looks sparse. Over time, some large groups began to emerge (in the center of

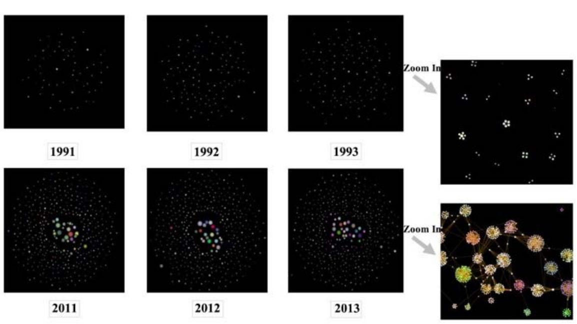


Fig. 7. The evolution of the topology of group network over time.

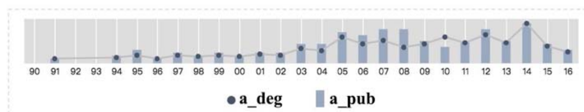


Fig. 8. The evolution of attributes of Prof. Hans-Peter Seidel from 1990 to 2016.

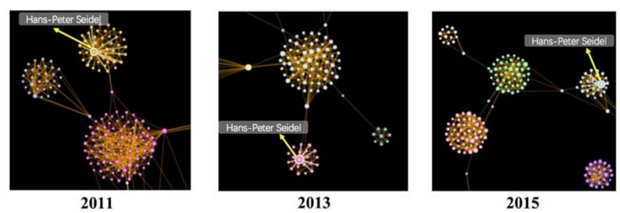


Fig. 9. Prof. Hans-Peter Seidel's position in the network in different years.

Similarly, we find this phenomenon in Prof. Qu's group, and go deep into group network and excavate the evolution rule of ego-centric network centered on him over time. In addition to 2005 and 2006, he has published papers between 2004 and 2016, and it shows an upward trend both in the number of papers published and the number of collaborators (Fig. 10(a)). What's more, the number of teams also shows a upward trend. This performance is consistent with Qu's own experience. In 2004, he graduated from the Stony Brook University and entered the Hong Kong University of Science and Technology. The first two years of research were mainly in the graphic field. In 2007, he began to pay more attention to research in the field of visualization and graphics. In 2015, he became a full-time professor at the HKUST. Although the number of collaborators and teams is on the rise, the network aggregation coefficient shows a downward trend (Fig. 10(b)). From the colors and connections of the nodes, it can be found that Qu has more consecutive collaborators, and in 2015 and 2016, more first-time collaborators appear (green nodes).

The nodes are laid out according to the total number of papers published, and the nodes under each time-slice are

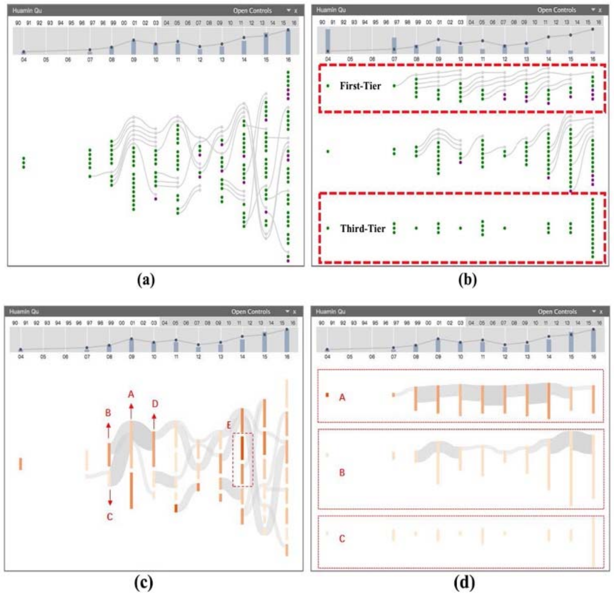


Fig. 10. The *Ego-centric Network View* of Prof. Qu. (a) the *Ego Attribute Evolution Module* of Qu; (b) by filtering, Qu's collaborators divided to three levels; (c) the *Community View* of Qu*; (d) the Community View* corresponding to (b).

divided into three stacks (Fig. 10(b)). We can see that there are more low-yield collaborators in 2016. This may be because many students have just entered the field this year. And Qu's high-yield collaborators are relatively more.

When we switch to the *Community View* (Fig. 10(c)), we can find more interesting things. After 2007, the number of communities that have cooperated with Qu is more than two. In 2012-2016, the number of communities has been increasing year by year. Meantime, new communities are formed almost every year (without inflow stream). For non-newly formed communities, their formation and disappearance can be easily traced from the figure. As shown in Fig. 10(d), most of the members of community A come from the merger of communities B and C from the previous moment (2008), and general members enter community D in 2010. By the *Detail View*, this part of people is investigated and found that the members who led the community were mainly Qu graduate students, doctoral students, or research assistants. In 2010, many students graduated and left, which can explain why the community disappeared.

From the distribution of Qu's community attributes, the average output of different communities shows some rules. As shown in Fig. 10(c), new communities or communities where there are more new collaborators (without inflow stream or inflow stream is thin), the nodes are often lighter in color, indicating that the average output of the community is less. We speculate that the possible cooperative group with Qu is related to his students (the academic ability was weaker when they first entered the field). However, there are also some communities that are not consistent with the above-mentioned performance. Community E in the figure, although there is no inflow stream, has a higher per capita output. It can be speculated that such community members are likely not to be the same agency as Qu. The survey was conducted through the *Detail View*. The guess was verified. Most of the members were from Peking University and Zhejiang University, and Qu is probably a participant rather than a leader in these communities.

From the connection in Fig. 10(a), it can be easily found that Conglei Shi and Qu maintain the longest continuous cooperation time (2011-2016). Yingcai Wu is the author who has spent the most time with Qu. He collaborated with Qu for the first time in 2007. He has worked continuously for four years until 2010, and has had intermittent cooperation in 2012-2016. This is exactly in line with Wu's personal career experience. As shown in Fig. 11, according to the layout of nodes based on the annual number of papers published by the author (a_pub), it can be seen that in the past few years of cooperation, Wu's number of annual publications has risen to a gradual stabilization process.

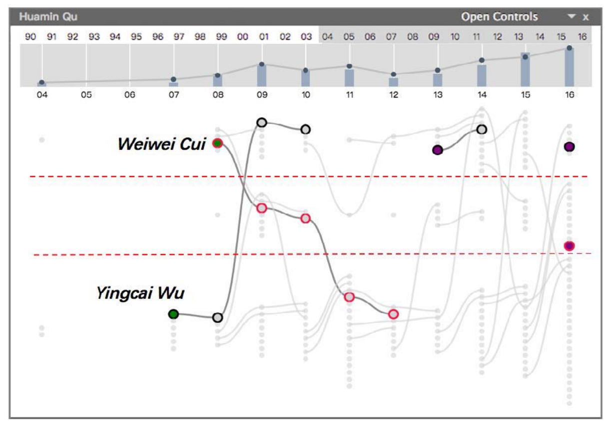


Fig. 11. Select interested collaborators for comparative analysis in the *Ego-centric Network View* of Qu.

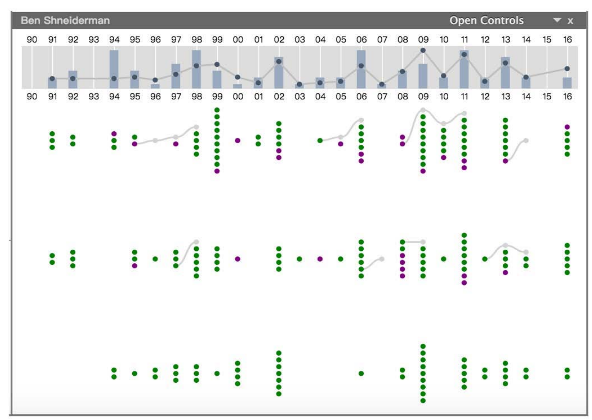


Fig. 12. The *Ego-Centric Network View* of Prof. Ben Shneiderman.

For the sake of simplicity, we choose Ben Shneiderman, who is more advanced in the *Weighted Attribute Sorting View*, to compare with Qu. Compared with Qu, Prof. Shneiderman's number of annual publications and the number of collaborators fluctuate from top to bottom, and does not show a clear trend (Fig. 12). From the node color, it can be found that the vast majority of the members are new collaborators. There are few consecutive collaborators, but there are more overall high output collaborators. Shneiderman is an early researcher who has entered the field of visualization and has a very high reputation in the visualization world. Unlike Qu's main collaborators are his students, Shneiderman's collaborators are more researchers seeking cooperation from other agencies. Therefore, the cooperation team is relatively fragmented and there are fewer continuous collaborators.

VI. Conclusion

Dynamic multivariate network data has become a more common type in real life. We have developed the visual analytics system DMNEVis that combines human and machine intelligence to discover evolution. And its availability and effectiveness have been verified in this paper. Although the rendering speed is now in seconds, the user experience needs to be improved for different configurations. What we need to do next is to improve the scalability and rendering speed of the data, provide more flexible operations based attributes layout and explore more applications.

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