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Dynamic Networks Visual Analytics: Approaches to facilitate visual analysis of complex and dynamic network data

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National Institute of Informatics
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Dynamic Networks Visual Analytics: Approaches to facilitate visual analysis of complex and dynamic network data

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1 Introduction

There is an abundance of complex dynamic data across many domains. Often such data has a natural interpretation as a network, e.g. for applications in the life sciences, the social sciences, telecommunication, finance, energy, and information security. Analysis of these dynamic networks is key to the understanding of complex processes both in fundamental research and for decision making.

Many of these cases require a human in the loop to make decisions, e.g. in emergency situations, or to allow experts to guide exploration and insight generation for complex processes. Lack of sufficient a priori knowledge, in combination with the complexity of the dynamics in multi-variate data, hamper the use of purely rule-based systems for analysis and decision making. Thus, a visual analytics type approach is best suited for such cases. Efficient tools and methods for the visual analysis of network changes will facilitate the human understanding of dynamic networks, but the complexity and the volume of the network dynamics pose a challenge to research.

Several research directions are concerned with the development of methods to support the analysis of such data, including machine learning, information and data visualisation, data analytics and human computer interaction.

Automated analysis methods help to guide the human expert, to filter and select relevant parts of the data space, and to detect patterns and trends. Interactive visualizations of both input data and analysis results need to support the user's perception and reasoning, and can lead to a better understanding and deeper insight. For that to happen, the visualisation and interaction concepts need to allow a faithful representation of the data and provide intuitive and efficient orientation and navigation in the data space.

While the visual analysis of big and complex static networks already poses a challenge for current research, the temporal aspect of dynamic networks adds a further difficulty that requires dedicated approaches for visualization, algorithmic treatment, and interaction. An important aspect that needs to be considered in the development of efficient concepts for practical applications is that the representations and interactions need to be tailored towards the actual use-case. In a similar way, network analysis methods need to be adapted to online streaming scenarios and the potentially huge data volumes. Knowledge discovery methods need to cope with large amounts of streaming data, but also with potential uncertainty and incompleteness of processed data.

The development of efficient methods for dynamic network visual analytics thus requires a multi-disciplinary approach that spans not only the classical disciplines related to data visualisation and interaction, visual analytics, information visualisation, and graph drawing, but also includes data sciences and network analysis. While researchers in all these fields tackle the problem of dynamic network analysis, we feel that a concerted effort will be best suited to advance the current state and will lead to new fruitful collaborations. The seminar has the aim to bring together experts in the listed fields and people from application areas to first have an exchange across the fields on the state of the art and current challenges, and then to state and tackle the most pressing research questions.

The main aims of the seminar were to

- bring together researchers from several communities that can contribute to dynamic network visual analytics research,
- identify core challenges based on both ongoing research and real-world examples, e.g. regarding computational efficiency, visual complexity, and interaction,
- examine where existing approaches can be extended and where completely new methods need to be developed to cope with the recent huge rise in complexity, velocity and volume of dynamic network data,
- investigate the embedding of dynamic network data and visualizations into the interfaces and visualizations commonly used in practice today,
- study efficient scalable approaches.

2 Program and Schedule

The seminar's schedule reflected the main goals of the meeting, with introductory talks to give an overview on the research fields and application areas covered by the participants. However, most time was devoted to discussions in small groups focusing to investigate the research questions and challenges of dynamic network analytics. The participants defined topics for working groups in an open discussion, and afterwards selected working groups based on their personal preference. Thus, the main part of the seminar time was used for the work in those groups, with a few general discussion sessions in between working group sessions, see Table 1.

The following overview talks were given:

- Daniel Archambault talked about animation, small multiples, and the mental map in dynamic graphs.
- Fabian Beck and Michael Burch presented the state of the art in visualizing dynamic graphs based on their STAR report on the topic.
- Ken Wakita presented an approach on how to fill the gap between theory and code.

Sunday	Check-in and welcome reception
Day 1:	Seminar start, welcome, introductory presentations, and working groups
09:00:	Opening, seminar overview by the organizers, and individual self-introductions by participants
10:00:	Break
10:30:	Invited Talks (Fabian Beck, Michael Burch, Ken Wakita)
12:00:	Lunch
13:30:	Invited Talk (Daniel Archambault)
14:30:	Plenary discussion - formulation of challenges and research questions
15:00:	Break
15:30:	Plenary discussion
18:00:	Dinner
Day2:	Working groups, discussions and presentations
09:00:	Lightning talks
09:15:	Breakout groups - tackling selected topics
10:30:	Break
11:00:	Working groups
12:00:	Lunch
14:00:	Working groups
15:30:	Break
16:00:	Working groups and group reports
18:00:	Dinner
Day3:	Working groups, discussions, and excursion
09:00:	Working groups
10:30:	Break
11:00:	Working groups
12:00:	Lunch
13:30:	Excursion
19:00:	Banquet
Day4:	Working groups and wrap-up
09:00:	Working groups
11:00:	Final group feedback and wrap up
12:00:	Lunch – end of the seminar

Table 1: Seminar schedule

3 Working Group Reports

3.1 Visual Analytics

Participants: Fabian Beck, Maxime Cordeil, Leszek Gąsieniec, Carsten Görg, Masahiko Itoh, Kwan-Liu Ma, Tobias Schreck, and Ken Wakita

Summary. Visual analytics integrates visualization approaches with algorithmic solutions and embeds them into highly interactive tools. This facilitates computer-supported, but still interactive analysis methods and makes data analysis more scalable. While various visualization techniques have been proposed for dynamic graph visualization already (Beck et al. 2016 [3]), very few visual analytics systems incorporate these techniques. In this working group, we analyzed existing approaches and developed a visual analytics process that could form the basis for a new generation of approaches to visually analyze dynamic graphs. We discussed a set of three realistic application scenarios and identified main research challenges for instantiating the process in these scenarios.

Previous Work. Traditionally, dynamic graph visualization techniques focus on graph layout and the visual encoding of the graph and time information. Only recently, some approaches have started to study interaction techniques and semi-automatic analysis methods in the context of dynamic graphs. Abello et al. (2013) [1] use interactively controllable degree-of-interest (DOI) functions to filter down a larger dynamic network (in particular, a co-author network). Liao et al. (2013) [5] detect anomalies in dynamic graphs leveraging a set of overview and detail visualizations. Li et al. (2013) [4] visualize the dynamic propagation of microblog messages through a network of users by different interactive temporal node-link visualizations. Some approaches also cluster similar subsequent time steps to simplify the time dimension (Bach et al. 2015 [2], von Landesberger et al. 2016 [6]).

Visual Analysis Process. In a realistic setting, graphs are often too large to be visualized as a whole especially if they undergo dynamic changes. However, when solving a specific task, there usually exists a natural focus that allows reducing the data to a smaller size. Hence, we want to leverage this natural focus to interactively filter the data according to the current needs of the analyst. In particular, a visual analysis system should support the following generic process, with the fourth step as an optional extension:

1. Define a specific (structural and temporal) pattern.
2. Browse the detected results in an overview visualization.
3. Select one result and view a focused dynamic graph visualization.
4. ⟨*Change the data and predict the impact of the changes.*⟩

This process is different from most related interactive analysis approaches, where usually the full graph is visualized as part of an aggregated overview and then interactively explored without support for detecting patterns. The approach by Abello et al. (2013) is most related, but the analyst cannot browse different results of the analysis individually. Figure 1 illustrates this process in a broader setting. The user is in control of the process, in particular, the dynamic graph data that might be aggregated from different data sources, the algorithmic analysis that helps retrieve patterns and trends, and the resulting dynamic graph visualization. Detected patterns set a focus in the analysis, while the full, but partially aggregated data provides a context for the visualization.

Specific tasks that an analyst has to perform as part of the process are, among others,

- to visually seek patterns or to interactively define them, to set a focus or points of interest in the data,
- to detect and explain trends, abnormal situations, outliers, temporal paths, or information propagation through the network,

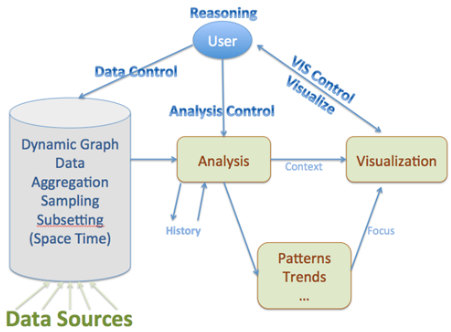


Figure 1: Visual analysis process

- to consider structural and temporal uncertainty of the analysis, and
- to predict future states of the graph.

Special examples of the process could implicate additional tasks, for instance, in scenarios like collaborative analysis and crowdsourcing as well as in-situ analysis (i.e., on-the-fly analysis of big data). Application Scenarios To concretize and specify the visual analysis process further, we discussed the following three realistic applications, including online scenarios where data is visualized in real time and offline scenarios where a retrospective analysis allows an in-depth investigation.

- Traffic data: Analyzing real-time traffic data such as passengers of a metro system requires online investigation of dynamic traffic flow through a network. In particular, during outstanding events such as the breakdown of a line, the operator of the traffic system relies on an effective visualization of the current situation and its evolution.
- Social media and co-author networks: The analysis of text documents and messages could help estimate impact of key players, specific events, or topics. For example, the visualization of a dynamic co-author graph would enable hiring committees and research managers to evaluate researchers and research meetings.
- Software engineering: Dependencies in a software system might violate design rules and could hinder an effective maintenance of the system, for example, unwanted cyclic dependencies. Identifying these patterns and understanding their creation by investigating their evolution would help improve the architecture of the software.

In these scenarios, the data is sufficiently large and complex that it often cannot be visualized as a whole. Hence, they would particularly profit from our visual analytics process that interactively filters and queries the data to smaller subsets.
Research Challenges. Based on the specified visual analysis process and discussed application scenarios, we derived central research challenges that will be important for developing novel visual analytics approaches for dynamic graphs.

- How to interactively specify patterns in a dynamic graph? – The basis for the exploration process is the interactive specification of temporal and structural patterns in dynamic graphs. While the design space of such patterns is large, first meaningful patterns can be derived from conceptual patterns described in different application areas, for instance, bad smells in software engineering, types of researchers in scientometrics, or social network metrics in social sciences.

- How to visualize a dynamic graph with (temporal/structural) focus-context and uncertainty? – A specific pattern sets a temporal and structural focus within the graph. When visualizing this, also some structural context needs to be provided on a coarser level. Hierarchical graph aggregation can be leveraged for summarizing the context. Visual comparison of related graphs could illustrate similar results or uncertain information.

- How to control time (real-time data + analysis time) in an online scenario? – The interactive analysis introduces a second time dimension. If information comes in too quickly in an online scenario, the update process could be stopped. This would simplify the problem to an offline scenario that can be handed over from an online operator to an offline analyst. Alternatively, an automatic approach monitors the real-time data, detects importants events, and notifies an analyst when further analysis is required. The appropriate automatic detection of interesting events in a dynamic graph may also allow to temporally compress (or abstract) the dynamic graph, or implement dynamic focus+context techniques.

Depending on the chosen application scenarios, all three challenges or a subset of them needs to be addressed to come up with an effective visual analysis approach. Apart from the relevance and quality of the proposed methods, we are also interested in the design of time and memory efficient algorithmic solutions.

Conclusion and Future Work. The group developed a generic analytics process for a new generation of visual analytics systems to study dynamic graphs. We described promising application scenarios and research challenges that might form the basis of such novel approaches. Group members plan to collaborate on developing such approaches and potentially refining the general visual analysis scenario.

References

[1] James Abello, Steffen Hadlak, Heidrun Schumann, and Hans-Jörg Schulz. A modular degree-of-interest specification for the visual analysis of large dynamic networks. *IEEE Transactions on Visualization and Computer Graphics*, 20(3):337–350, 2014.

[2] B. Bach, N. Henry-Riche, T. Dwyer, T. Madhyastha, J-D. Fekete, and T. Grabowski. Small multipiles: Piling time to explore temporal patterns in dynamic networks. *Computer Graphics Forum*, 34(3):31–40, 2015.

[3] Fabian Beck, Michael Burch, Stephan Diehl, and Daniel Weiskopf. A taxonomy and survey of dynamic graph visualization. *Computer Graphics Forum*, 2016.

[4] Quan Li, Huamin Qu, Li Chen, Robert Wang, Junhai Yong, and Detan Si. Visual analysis of retweeting propagation network in a microblogging platform. In *Proceedings of the 6th International Symposium on Visual Information Communication and Interaction*, VINCI '13, pages 44–53, New York, NY, USA, 2013. ACM.

[5] Q. Liao, L. Shi, and C. Wang. Visual analysis of large-scale network anomalies. *IBM Journal of Research and Development*, 57(3/4):13:1–13:12, May 2013.

[6] T. von Landesberger, F. Brodkorb, P. Roskosch, N. Andrienko, G. Andrienko, and A. Kerren. Mobilitygraphs: Visual analysis of mass mobility dynamics via spatio-temporal graphs and clustering. *IEEE Transactions on Visualization and Computer Graphics*, 22(1):11–20, Jan 2016.

3.2 Scalability

Participants: Daniel Archambault, Michael Burch, Markus Chimani, Peter Eades, Hiroshi Hosobe, Karsten Klein, Kazuo Misue, Hsiang-Yun Wu, Xiaru Yuan

Summary. Due to the volume, velocity, and complexity of today's data sets in practical applications, scalability is an important aspect in the development of visual analytics approaches for dynamic graph analysis. Scalability poses a big challenge for current research and for applications in practice. For many applications, e.g. from the life sciences, it is impossible with current methods to even process the complete data stream, or to solve analysis problems to optimality.

In this working group we analyzed the characteristics of scalability in the dynamic graph context, tried to define dimensions of it, discussed requirements from application areas, and finally focused on selected challenges.

Discussion. A large part of the discussions was centered around the definition of aspects or dimensions of scalability. There are some commonalities of the general big data characterisation and dynamic networks scalability. Our first approach contained four main dimensions that we thought might be necessary to characterise dynamic data for a discussion of scalability issues.

- Mass - defined on the graph structure and the data annotations, e.g. number of nodes and edges
- Momentum - the relative size of the change, or $mass * velocity$
- Potential - similar to the concept in computational complexity, the potential was meant to measure some amortized complexity of the data over several updates
- Velocity - the speed at which changes happen, i.e. $\frac{\Delta G}{\Delta t}$

After some discussion we dropped 'potential' again as it didn't seem to fit as a reasonable dimension and probably would have to be adapted to a particular use-case. We agreed that there needs to be a distinction of visual and processing scalability to cover the difference in computational and human capabilities. While hardware and software improvements can advance the limits of what is computationally tractable, the limitations of e.g. human perception represent a much stricter constraint for visual analytics approaches.

A further focus was on what we called "phase transitions" in complexity dimensions, were we would expect rifts in the efficiency and efficacy of methods for visualization and analysis, such that visual analytics concepts need to be adapted to handle data in a different way depending on the area of the data space it belongs to. In particular, we looked at the relation between velocity and mass of the dynamic data, and investigated the regions of the mass-velocity coordinate system with regard to the applicability of visualisation and analysis techniques. Our hypothesis is that, while there is no simple mapping of techniques to locations in the coordinate system, there is a sweet spot that enables good visualisation, i.e. where common approaches might already be sufficient. For the other areas dedicated solutions will be required that depend on the actual velocity and mass values. These solutions will include preprocessing methods that allow to transform the input data such that it is 'shifted' towards the visualisation sweet spot, e.g. by means of aggregation of time like subdivision, clustering, or interval aggregation.

Finally, we listed specific challenges, including the 'shape' of a clustering, the characterisation of 'temporal motifs', and how changes can be clustered, and addressed them for the remainder of the working group discussions. We discussed possible approaches for clustering of changes as well as time filtering and distortion, e.g. with a "time lens"-based approach.

For future work, we plan to work on one of those challenges in more detail in order to develop a model and method that can be applied in practice.

3.3 Real World Applications

Participants: Takayuki Itoh, Stephen Kobourov, Björn Sommer Guest participants: Kwan-Liu Ma, Xiaoru Yuan

Summary. The smallest group of the Shonan meeting on "Dynamic Networks Visual Analytics" discussed a number of application areas and related topics.
Topic. The main topic for this group was to discuss real-world applications which require visualization of dynamic networks. We identified several areas: Biomedicine, Co-Authorships, Computer communication/relation, Human communication/relation, Financial Transaction, Retweet Maps/Microblog, Surveillance, Transportation/Traffic. For more information, please see the application areas overview list below.

Application Areas Overview.

- Biomedical networks
  - Neuronal Networks
  - Health-related Network
  - Cell Networks
  - Biomolecular Networks
- Co-Authorship Networks (growing-only)
- Computer communication/relation Networks
  - eCommunication Crimes/Online Fraud Networks
  - Internet Security Networks
  - Supercomputer Communication Networks
- Financial Transactions Networks
  - Bitcoin Network
  - Stock market
- Human communication/relation Network
  - Development of Keywords (growing-only)
  - Conference analysis, change in paper topics

- Wordle

- Retweets Maps/Microblog (China) Diffusion Map (growing-only)
  - Social networks
- Surveillance Networks
  - International travel data
  - Movement of humans recorded by sensors
- Transportation/Traffic Networks
  - Airplane trajectories

We also discussed some specific goals for dynamic network visualizations, as well as specific tasks one might perform with dynamic network visualizations. Examples of such goals include present, explore, monitor, compare, and verify hypothesis. Examples of such tasks include find patterns, find correlations, find outliers, find trends, find structural changes, and find temporal changes.

Attributes. In addition we started to identify a list of attributes which apply to a number or all of the aforementioned areas, namely Structural Changes, Temporal Changes, Fixed Layout, Statistics, and Simulations. By discussing the different associated application areas, we found out that one attribute which all areas have in common are the Temporal Changes. On the other hand, the attribute Fixed Layout seems to be quite specific for Transport/Traffic N., and might be also interesting for Biomedicine and Human communication/relation N. Please see the complete table of dynamic network application areas in Figure 2.

Attributes	Dynamic Network Application Areas					
	Biomedicine	Computer communic./ relation	Financial Transactions	Human communic./ relation	Surveillance	Transport/ Traffic
Structural Changes	X			X	X	X
Temporal Changes	X	X	X	X	X	X
Fixed layout	(X)			(X)		X
Statistics	X		X		X	(X)
Simulations	X	X	X			X

Figure 2: A tabular overview of discussed application areas. (X - regular attributes, (X) - optional attributes

Target Audience. Another important topic during the discussion were the different target groups - from a qualitative and quantitative point of view. We identified three groups: domain experts, general scientists, and the general public. Whereas the domain expert should be able to edit the data, the general scientist should be able to use dynamic networks visualization in discussions, publications and presentations, and finally the general public should be able to read and interpret the presented data. Depending on the target group, the design of the dynamic networks could differ dramatically. In addition, the quantitative perspective can be very important: are the dynamic network visualizations directed towards a large or small audience? This might be especially relevant in terms of performance issues and interaction (e.g., comment function) with the data.

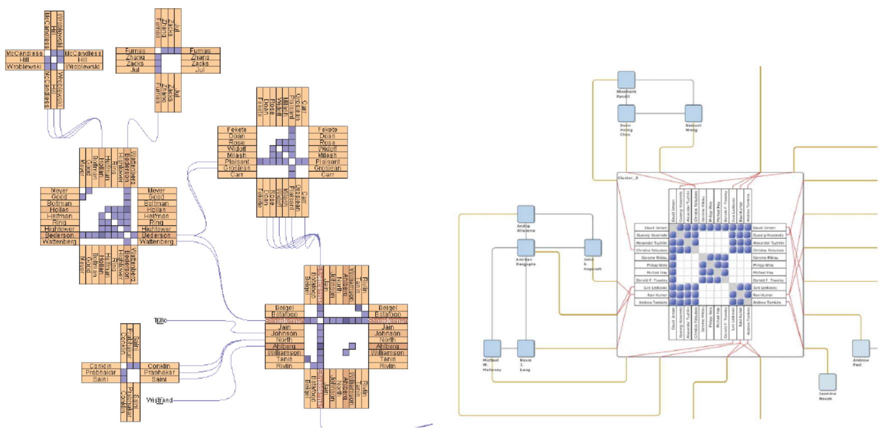
Generating dynamic networks and a tool to visualize them. Another topic which might be interesting for future collaboration is the development of a new tool to generate personal dynamic graphs - available especially to the general public. We considered several ideas for different types of personal data that can be visualized with dynamic networks, such as personal web activity (visited pages, visit duration, temporal as well as structural patterns). Another possibilty would be to extract dynamic networks from celebrities (e.g., retweet networks, topics over time, etc.)

Future Work. A better understanding of the real-world need for dynamic network visualization can help in writing convincing research proposals. A tool for generating personalized dynamic networks will raise awareness and spur more work in this area.

4 Dynamic Approaches for Hybrid Visualizations

Participants: Vladimir Batagelj, Emilio Di Giacomo, Walter Didimo, Michael Kaufmann, Giuseppe Liotta, Maurizio Patrignani

Summary. Hybrid Visualization is a paradigm invented to support the visual analysis of large and complex networks. It mixes node-link diagrams and matrix-based representations in a single visualization. Dense subgraphs are visualized with a matrix-based representation, while sparse subgraphs or high-level views are shown by means of a node-link diagram. An example of a hybrid visualization taken from the seminal paper of Henry et al. [15] is shown in Figure 3a.



(a) (b)

Figure 3: Two examples of hybrid visualizations: (a) NodeTrix (b) VHyXY.

In a subsequent paper, Batagelj et al. [8] proposed an algorithmic framework called (X,Y)-*clustering* and describe a hybrid visualization system called VHyXY based on this approach (see Figure 3b for an example of a visualization created by VHyXY). An (X,Y)-clustering of a graph G is a clustering of G such that the graph induced by each cluster belongs to a given family X and the inter-cluster graph belongs to another given family Y. The inter-cluster graph is represented as a node-link diagram (for example it could be a planar drawing if Y is the family of planar graphs), while each cluster is represented as a matrix or again as a node-link diagram, depending on its density or user's preference. Given this framework, the concept of *k-cores* is exploited to define the clusters of a given graph G; the k-core of G is the largest subgraph of G such that all the nodes in such a subgraph have degree at least k (with $0 \leq k < |V|$). For each node v in G, the *core number of v* denotes the largest k such that a k-core exists and contains v. Each connected component of the k-core of G is called a *k-core component* of G. Batagelj et al. [8] use the k-core components of G to define the clusters of G. Each cluster (i.e., each k-core component) can then be recursively decomposed by using larger values of k. The clustering of G computed in this way is called a *k-core decomposition* of G, and the tree that describes such a decomposition is called a *k-core decomposition tree*. An example of a k-core decomposition of a graph is shown in Figure 4.

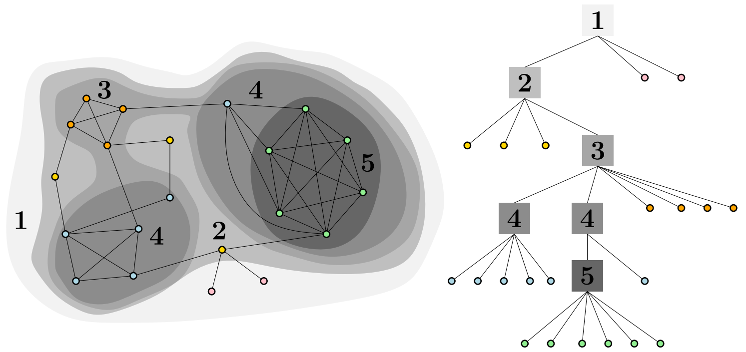


Figure 4: A k-core decomposition of a graph and the corresponding k-core decomposition tree.

We recall that the notion of k-core was introduced by Seidman in 1983 [19], and used in several application areas for the decomposition and the analysis of large graphs, especially in the field of social networks and biology (see, e.g., [9, 11, 13, 14, 17, 20]). A linear-time algorithm to compute the core number of each vertex of a given graph has been proposed by Batagelj and Zaveršnik [10]. We finally remark that hybrid visualizations have been recently studied from a theoretical point of view by Da Lozzo et al. [12].

Our algorithmic problem. We studied the problem of efficiently updating the k-core decomposition tree under edge insertions and deletions. This is a key algorithmic problem for the design and implementation of a hybrid visualization system based on the k-core decomposition where the visualized network can change dynamically. We concentrated on the following questions: (i) Is it possible to guarantee sub-linear time per operation (asymptotically speaking, according to a worst-case analysis)? (ii) If linear-time is required in the worst case, can we design techniques to speed-up the computation in practice?

The problem of efficiently updating the core numbers of the vertices dynamically, has been recently studied in various papers [7, 16, 18, 21]. It is worth remarking that the algorithms presented in these papers do not guarantee sub-linear time per operation, but are fast in practice. On the other hand, they only concentrate on updating the core numbers of the vertices, while we want to keep the k-core decomposition tree updated. Indeed, the dynamic maintenance of the different connected components of every k-

core, seems to be a more challenging problem

We devised a possible algorithm for our problem. The main idea is to use a suitable data structure to efficiently find the components that are affected by the edge addition/removal and to locally change the k-core decomposition tree to keep it updated. The worst-case time complexity is still linear but we hope that the algorithm could be faster in practice. We plan to further refine the algorithm and to experimentally test it to evaluate its performance. Moreover, we would like to design a dynamic hybrid visualization system based on our algorithm.

References

[7] Sabeur Aridhi, Martin Brugnara, Alberto Montresor, and Yannis Velegrakis. Distributed k-core decomposition and maintenance in large dynamic graphs. In *Proceedings of the 10th ACM International Conference on Distributed and Event-based Systems*, DEBS '16, pages 161–168, New York, NY, USA, 2016. ACM.

[8] V. Batagelj, F. J. Brandenburg, W. Didimo, G. Liotta, P. Palladino, and M. Patrignani. Visual analysis of large graphs using (X, Y)-clustering and hybrid visualizations. *IEEE Transactions on Visualization and Computer Graphics*, 17(11):1587–1598, Nov 2011.

[9] Vladimir Batagelj, Andrej Mrvar, and Matjaž Zaveršnik. Partitioning approach to visualization of large graphs. In Jan Kratochvíl, editor, *Graph Drawing: 7th International Symposium, GD'99 Štiřín Castle, Czech Republic September 15–19, 1999 Proceedings*, pages 90–97, Berlin, Heidelberg, 1999. Springer Berlin Heidelberg.

[10] Vladimir Batagelj and Matjaž Zaveršnik. Fast algorithms for determining (generalized) core groups in social networks. *Advances in Data Analysis and Classification*, 5(2):129–145, 2011.

[11] G. J. Baxter, S. N. Dorogovtsev, A. V. Goltsev, and J. F. F. Mendes. k-core organization in complex networks. In T. My Thai and M. Panos Pardalos, editors, *Handbook of Optimization in Complex Networks: Theory and Applications*, pages 229–252. Springer US, Boston, MA, 2012.

[12] Giordano Da Lozzo, Giuseppe Di Battista, Fabrizio Frati, and Maurizio Patrignani. Computing nodetrix representations of clustered graphs. In Nöllenburg Martin and Yifan Hu, editors, *Graph Drawing and Network Visualization: 24th International Symposium, GD 2016*. Springer International Publishing. to appear.

[13] Marco Gaertler and Maurizio Patrignani. Dynamic analysis of the autonomous system graph. In *International Workshop on Inter-domain Performance and Simulation (IPS)*, pages 13–24, 2004.

[14] A. V. Goltsev, S. N. Dorogovtsev, and J. F. F. Mendes. k-core (bootstrap) percolation on complex networks: Critical phenomena and nonlocal effects. *Phys. Rev. E*, 73:056101, May 2006.

[15] N. Henry, J. D. Fekete, and M. J. McGuffin. Nodetrix: a hybrid visualization of social networks. *IEEE Transactions on Visualization and Computer Graphics*, 13(6):1302–1309, Nov 2007.

[16] R. H. Li, J. X. Yu, and R. Mao. Efficient core maintenance in large dynamic graphs. *IEEE Transactions on Knowledge and Data Engineering*, 26(10):2453–2465, Oct 2014.

[17] Tomasz Łuczak. Size and connectivity of the k-core of a random graph. *Discrete Mathematics*, 91(1):61 – 68, 1991.

[18] Ahmet Erdem Saríyüce, Buğra Gedik, Gabriela Jacques-Silva, Kun-Lung Wu, and Ümit V. Çatalyürek. Streaming algorithms for k-core decomposition. *Proc. VLDB Endow.*, 6(6):433–444, April 2013.

[19] Stephen B. Seidman. Network structure and minimum degree. *Social Networks*, 5(3):269 – 287, 1983.

[20] Stefan Wuchty and Eivind Almaas. Peeling the yeast protein network. *PROTEOMICS*, 5(2):444–449, 2005.

[21] Yikai Zhang, Jeffrey Xu Yu, Ying Zhang, and Lu Qin. A fast order-based approach for core maintenance. *CoRR*, abs/1606.00200, 2016.

5 Participants

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- Hsiang-Yun Wu, Keio University
- Xiaoru Yuan, Peking University
- Hsu-Chun Yen, National Taiwan University

6 Overview of Talks

There were three invited talks, giving rather broad overviews on different aspects of the visual analytics challenges, see the abstracts below. In addition, two lightning talks were given.

Daniel Archambault

Animation, Small Multiples, and the Mental Map in Dynamic Graphs

Visualising dynamic graphs is important for many application areas. For social media networks, these visualisations can help us understand the interaction and interests of users online. In biology, they can illustrate the interactions between genes and biological processes. Understanding and designing effective visualisation methods for dynamic network data is fundamental to these areas as well as many others. In the talk presented at Shonan, the results of three experiments was presented covering the effective presentation of dynamic networks. In particular, results with respect to animation (presentation of interactive movies of the data), small multiples (presenting the data through several linked windows like a comic book), and drawing stability (the visual stability of the data presentation).

Given the evidence provided by these three experiments, some guidelines for the effective presentation of dynamic graphs were drawn. The mental map, or drawing stability, is important when a large number of objects could be of interest to the task and highlighting of these objects (via colour or other means) is difficult or not possible. Stable drawings help users orient themselves in dynamic data (to find specific locations in the graph or to follow specific paths) and do not necessarily improve readability. Animation can be useful if changes are over a short time period (two to three timeslices), the data is not stable in terms of spatial position (many objects must move), and highlighting is not possible by other means. Otherwise, static presentations, like small multiples, have significant advantages in terms of the time it takes to used them. They often have significantly faster response times with no significant differences in terms of error rate. For long time series, there is a significant research opportunity for the design and implementation of visualisation methods that effectively scale to long time series.

Ken Wakita

Filling the gap between theory and code

The problem of finding a good layout for graphs, including dynamic graphs, is understood as optimization of objective functions that encodes visual cosmetics, meeting various constraints. The cause of the complexity of maintaining software implementation of graph layout algorithms is primarily due to semantic gap between the high-level, mathematical description of the layout problem and low-level description of the software using programming languages. The talk addresses this problem by describing the algorithm using computational algebra system and automatically synthesizing the software and its documentation from the description.

Fabian Beck, Michael Burch

Title: The State of the Art in Visualizing Dynamic Graphs

Visualizing changes in graphs and networks is a growing area of research with a variety of approaches to encode the graph structure and its temporal evolution. We report the state of the art in the field by introducing a taxonomy that structures existing techniques. The representation of time as animation (time-to-time mapping) or timeline (time-to-space mapping) forms the first discriminating feature of the hierarchically structured taxonomy. In the talk, we present the structure of the taxonomy and provide examples for every taxonomy category. Furthermore, we discuss main results of conducted user evaluations and promising future directions of research.

Lightning talks

Carsten Goerg: Matching the user's mental map Traditionally, researchers are concerned about preserving the user's mental map when drawing dynamic graphs. They try to keep the parts of the layout for which the underlying graph doesn't change stable, and only change the parts of the layout for which there are changes in the underlying graph. In some domain applications there exist a similar challenge, even for static graphs. Sometimes, a user already has a mental map for a network that represents a specific set of relationships. In these scenarios, it is important that the generated layouts match the user's mental map to minimize the user's efforts of understanding the visualization. I present such a scenario in the biomedical domain and propose a semi-automatic layout approach that can address the problem of matching the user's mental map.

Huamin Qu: Overview on recent research

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