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Trends and Perspectives in Graph Drawing and Network Visualization

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Trends and Perspectives in Graph Drawing and Network Visualization

Organizers:

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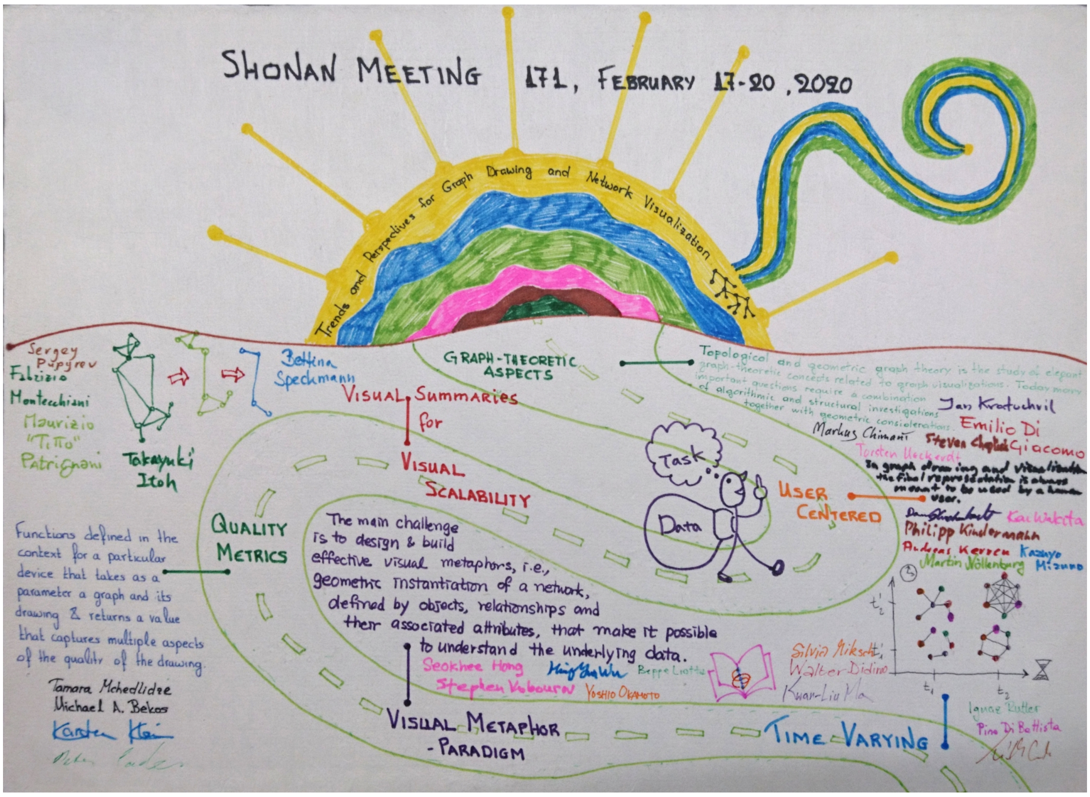

1 Summary

Graph Drawing (GD) concerns geometric representations of graphs and networks and is motivated by applications requiring structural information to be visualized as graphs. This research area emerged as an independent discipline in the early 1990's and is positioned at the intersection of different areas, such as graph algorithms, geometric computing, and interactive system design. The co-existence of combinatorial problems with questions from software engineering and experimental algorithmics within graph drawing makes it an extraordinary melting pot where theorists and practitioners can meet and share their knowledge. Indeed, the use of graph drawing approaches to present and visually analyze networked data sets has become a cornerstone in how information and knowledge is conveyed to users in many application domains such as social sciences, biological networks, software engineering, and forensic criminology.

The strong interaction of theory and practice within GD is reflected, for example, by the dual nature present within the proceedings of the main GD conference (the International Symposium of Graph

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Drawing and Network Visualization[1]), by the papers published by the flagship journal of the area (the Journal of Graph Algorithms and Applications), and by the many books and handbooks devoted to the subject. A prime example of this specialty of GD are the force-directed algorithms that are arguably among the most popular graph layout techniques in the information visualization community and that are also an endless source of deep mathematical questions. Namely, from the algorithmic point of view, the pioneering paper by Tutte [Tut63], dating from the 1960's and describing a simplified force-directed model for graph drawing, has motivated a sequence of papers on convex straight line planar drawings of graphs. From the system design point of view, visual analytics systems that use force-directed approaches are continuously evolving to handle the increasing complexity and size of the data.

This is an important time to reflect on Graph Drawing. Not only has there been a vast expansion in the variety of ways networks are visualized (e.g., node-link diagrams, treemaps, hybrid visualizations, etc.), there has also been an explosion of the use of visual analytics as an essential ingredient in data science and information mining. These approaches are further being combined with new computational models arising from emerging architectural frameworks and infrastructures such as, for example, the streaming and the distributed models.

In this seminar we gathered a sample of experts in the field and through presentations (see Chapter 2) and discussions (as outlined below) identified a selection of important topics (see Chapter 3) with corresponding challenges for the future of graph drawing and network visualization. The topics we ended up focusing on included:

- Visual Metaphors: the different visual representations of networked information.
- Quality Metrics: the different measures associated with visual representations.
- Human-Centered Concerns: the importance of task-oriented design with Humans in mind.
- Dynamic Networks: while many now classic solutions exist for static networks, visualizing networks which evolve over time is only beginning to be understood.
- Visual Summaries: with the need for ever larger networks to be visualized but only limited screen space, methods for summarizing information are needed.
- Graph-Theoretic Considerations: the interplay between graph theory and network visualization is one with a long history and remains a top priority in the field.

Future Considerations: We feel that this meeting served as an excellent starting point for the conversation regarding the future challenges of graph drawing an network visualization. As a further outcome, we are working (together with all of the participants) toward a challenge manifesto to be published in a prominent journal. We note that topics beyond those discussed here also were present in the discussions of important challenges and we have included a short overview of these below.

- Immersive Environments: The continuing advancement of virtual reality headsets promises to give us a truly immersive experience at an affordable price, which suggests us to rethink about 3D visualization of graphs and networks in an immersive environment. The problem of representing and interacting with large, complex networks in an immersive space to support a variety of exploratory and comparative network analysis tasks offers tremendous research opportunities. Innovations must be made in designing new layout methods, gesture-based interaction techniques, visual metaphors, etc.
- Aspects of Uncertainty in the Input: One is often faced with the task of visualizing information from unreliable sources. This comes with a myriad of challenges most of which remain unsolved, e.g., regarding whether to focus on visualizing the uncertainty itself, picking a "highly-likely" output, or some combination thereof.
- Multi-Layer Networks: The possibility of having different types of edges that describe different types of relationships on a same set of nodes poses the question of efficiently and effectively displaying different sub-networks on a same set of data. This question has motivated fundamental research (for example on simultaneous embeddings and on geometric thickness), experimental studies, and system development (concerned, for example, with the use of multi-layer visualizations for social network analysis).

[1] See `graphdrawing.org` for further information.

In conclusion, from our discussions during this meeting it is clear to us that a vast number of interesting challenges exists (well beyond those mentioned within this document). In particular, while we hope this this will serve as a helpful guideline regarding problems to pursue, we remark that this is certainly not meant to cover all of the challenges in the area of graph drawing and network visualization.

List of Participants:

- Daniel Archambault, Swansea University, UK
- Michael A. Bekos, Universität Tübingen, Germany
- Steven Chaplick, Maastricht University, The Netherlands
- Markus Chimani, Uni Osnabrück, Germany
- Giuseppe Di Battista, Università degli Studi Roma Tre, Italy
- Walter Didimo, University of Perugia, Italy
- Emilio Di Giacomo, University of Perugia, Italy
- Peter Eades, University of Sydney, Australia
- Seok-Hee Hong, University of Sydney, Australia
- Takayuki Itoh, Ochanomizu University, Japan
- Andreas Kerren, Linnaeus University, Sweden,
- Philipp Kindermann, Universtät Würzburg, Germany
- Karsten Klein, University of Konstanz, Germany
- Stephen Kobourov, University of Arizona, USA
- Jan Kratochvil, Charles University in Prague, Czech Republic
- Giuseppe (Beppe) Liotta, University of Perugia, Italy
- Kwan-Liu Ma, University of California Davis, USA
- Tamara Mchedlidze, Karlsruhe Institute of Technology, Germany
- Silvia Miksch, TU Wien, Austria,
- Kazuyo Mizuno, Yahoo Japan, Japan
- Fabrizio Montecchiani, University of Perugia, Italy
- Martin Nöllenburg, TU Wien, Austria
- Yoshio Okamoto, The University of Electro-Communications, Japan
- Maurizio (Titto) Patrignani, Università degli Studi Roma Tre, Italy
- Sergey Pupyrev, Facebook, USA
- Ignaz Rutter, Universtät Passau, Germany
- Bettina Speckmann, Eindhoven University of Technology, The Netherlands
- Csaba D. Toth, Tufts University, USA
- Torsten Ueckerdt, Karlsruhe University of Technology, Germany
- Ken Wakita, Tokyo Institute of Technology, Japan
- Hsiang-Yun Wu, TU Wien, Austria

Meeting Schedule:

- Feb 16 (Sun)
  - 19:00-21:00 Welcome Party
- Feb 17 (Mon)
  - 9:00-10:00 Introduction
  - 10:30-12:00 Summary talks
  - 13:30-15:30 Summary talks
  - 16:00-18:00 Topic discussion
- Feb 18 (Tue)
  - 9:00-10:00 Group forming
  - 10:30-12:00 Group discussion
  - 13:30-18:00 Group discussion
- Feb 19 (Wed)
  - 9:00-12:00 Group discussion
  - 13:30-20:30 Excursion and Dinner
- Feb 20 (Thu)
  - 9:00-10:30 Group discussion
  - 11:00-12:00 Group presentation

2 Invited Talks

In this chapter we provide the abstracts from the five invited talks that occurred during the first day of the meeting. These are listed in the order in which they occurred.

2.1 Morphing Planar Drawings of Graphs

Giuseppe Di Battista[a]

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Let Γ_0 and Γ_1 be two drawings of the same graph G. A *morph* between Γ_0 and Γ_1 is a continuously changing family of drawings of G indexed by time $t \in [0, 1]$, such that the drawing at time $t = 0$ is Γ_0 and the drawing at time $t = 1$ is Γ_1.

If both Γ_0 and Γ_1 have a certain geometric property (e.g. they are planar or their edges are straight-line segments) it is interesting, both from the theoretical and from the application points of view, that all the drawings of the morph *preserve* that property.

The problem of finding a morph between two drawings of the same graph that preserves one or more properties attracted the attention of several researchers since the first half of the twentieth century. As an example, Cairns in 1944 gave an algorithmic proof that a morph that preserves planarity of a triangulation always exists. Thomassen in 1983 extended the result to all planar straight-line drawings of embedded graphs.

Morphs that preserve a certain property can be classified from several perspectives. As an example they can be different in terms of vertex trajectories, in terms of vertex speed, in terms of number of steps, or in terms of arithmetic precision that is needed to compute the position of the geometric components of the drawings. We surveyed the state-of-the-art on this intriguing topic focusing the attention on morphs that preserve planarity.

2.2 The current state of Network Visualisation

Karsten Klein[a]

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A large amount of research has been dedicated to network visualisation over several decades, due to the importance of visual network analysis in a variety of application areas but also the beauty of the underlying research challenges. Topics of research span quite diverse aspects such as algorithmic complexity, design of layout methods, navigation, the mental map, and approaches for dynamic network representation. Some of the main challenges were in the research focus from the early beginnings, such as the quest for suitable quality measures, while others arose or changed over time based on the requirements from applications, such as the handling of large and dense graphs or the handling of restricting constraints for the visualisation.

In this talk, I give an overview on the main challenges in network visualisation as well as on the proposed solutions, and I present my personal view on the success or failure of the research community to tackle these challenges. This includes suggestions to increase the research effort in directions with the biggest gap between existing and required solutions, such as network comparison and representation of dynamic networks. In particular, I would like to increase the awareness for the requirement to test and confirm the suitability and efficiency of new methods in user studies, and suggest to explore how to explicitly include mechanisms of perception into the design of new approaches.

2.3 Multi-Level Graph Sketches

Stephen Kobourov[a]

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Graph sketching has become a fundamental technique for making polynomial time algorithms actually usable in practice. Here, a sketch of a large graph is a subgraph that preserves certain properties of the original graph. Examples are spanning trees and Steiner trees (preserving connectedness), graph spanners (preserving approximate pairwise distances) and spectral sparsifiers (preserving approximate graph spectra). Graph sketches are used in tasks such as network routing, robotics, and computational biology. We discuss work on computing multi-level graph sketches, focusing on a general framework of efficient algorithms and rigorous analysis of their theoretical properties. An example of this our approximation algorithm for the Multi-Level Steiner Tree problem. Another example is our approximation algorithm for the Multi-Level Graph Spanner problem. Finally, we also discuss multi-level graph layout algorithms that provide semantic zooming capabilities for interacting with large graphs.

2.4 Geometric Representations of Graphs

Jan Kratochvíl[a]

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We have mainly in mind *geometric intersection graphs*, i.e., classes of graphs that allow intersection representations of (typically two-dimensional) objects with specified geometric properties (such as connectedness and shape, properties preserved by some or all standard transformations such as translation, rotation, reflection or scaling). Perhaps the best known example are *interval graphs* (intersection graphs of intervals on a line) which find applications in such remote areas as scheduling, sociology or paleontology. Other examples include *circle graphs* (intersection graphs of chords of a fixed circle), *circular arc graphs* (intersection graphs of arcs of a fixed circle), but also *co-comparability graphs* which happen to be exactly the intersection graphs of graphs of continuous functions defined on the same interval (and therefore also referred to as *function graphs*). Classes of geometric intersection graphs are well studied both for their practical motivation and applications, and for algorithmic aspects. It turns out that many optimization problems which are hard (NP-complete) for general graphs are efficiently solvable (at least for some of) geometric intersection graphs. E.g., both CLIQUE and STABLE SET problems are solvable in polynomial time for the so called *interval filament graphs*, a large class of geometric intersection graphs that contains all of the above mentioned classes. However, the known algorithms require the input graph to be given with a representation, while it is known that to find an interval filament representation (if it exists) of a graph is an NP-hard problem. This shows that deciding if a given graph has a representation of a desired type is an important question, and it is typically referred to as RECOG(A) where A is the graph class under consideration. And indeed, for most classes of geometric intersection graphs which have been studied, the complexity of their recognition has been settled.

Recently two paradigms that generalize the question of recognizing such graph classes have been introduced. One is referred to as the *Partial Representation Extension Problem* and denoted by RepExt(A), the other one is the *Simultaneous Representation Problem*, denoted by SimRep(A). The input of RepExt(A) is a graph and an A-representation of a part of it, the task is to decide if this partial representation can be completed to an A-representation of the entire input graph. The input of SimRep(A) consists of several graphs with some common parts (often requested to be in the so called sunflower position, i.e., the intersection of any two of them is the same subgraph), and the task is to find A-representations of the graphs such that for any two of them, their common part is represented the same way.

Obviously, for any graph class A, both RepExt(A) and SimRep(A) are at least as difficult as RECOG(A). The complexity of these more general problems has been determined for only a few graph classes (for which recognition is polynomial time decidable), and as expected, in all cases the algorithms are much more complicated than the algorithms for recognition. However, it is somewhat surprising that in all cases where the complexity is known, the more general problems are still polynomial time decidable. Moreover, in all known cases, SimRep is at least as difficult as RepExt. These observations yield the following two metaproblems: 1) Are RepExt(A) and SimRep(A) polynomial time decidable for any class A of geometric intersection graphs which is recognizable in polynomial time? 2) Is SimRep(A) at least as difficult as RepExt(A) for any class A of geometric intersection graphs? Perhaps even SimRep with only two graphs on input?

Let us mention in conclusion that the concept of partial drawing extension and simultaneous drawings of graphs is well known and studied in Graph Drawing. In that area, there are examples known when partial drawing extension is provably more difficult than drawing from scratch (e.g., noncrossing straight line drawing of graphs in the plane).

2.5 Challenges and Future Directions for Graph Drawing – An Attempt at Exploring the Parameter Space

Martin Nöllenburg[a]

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In this talk, we first explore the interdisciplinary and multifaceted nature of graph drawing as a research field. In particular, it is positioned between graph theory and combinatorial geometry on the one side and network visualization on the other side. We argue that while having many self-motivated and curiosity-driven aspects, graph drawing benefits strongly from its external influences.

In the second part of the talk, we present a collection of parameters that can be used to define different types of graph drawing and network visualization research and open problems. For each parameter, we give some examples. The discussed parameters are:

1. **theory vs. practice**, e.g., the study of computational complexity aspects and combinatorial bounds vs. the implementation and evaluation of interactive visualization systems;
2. **layout quality vs. computational efficiency**, e.g., the degree of optimizing a quality measure vs. the asymptotic or empirical performance of a layout algorithm;
3. **specific graph classes vs. general graphs**, e.g., the study of planar graphs, trees, beyond-planar graphs etc. vs. arbitrary (un-)directed graphs;
4. **small/sparse graphs vs. big/dense graphs**, e.g., whether the focus is on an exact, detailed layout of a small graph or on a higher-level overview of a big graph;
5. **static vs. dynamic graphs**, e.g., whether a single layout is of interest or a sequence of temporal graphs should be drawn;
6. **abstract vs. multivariate graphs**, e.g., whether a plain node-link diagram with points and curves is drawn or a complex real-world network with various vertex and edge attributes;

7. **single vs. multilayer graphs**, e.g., whether the layout is for a single graph or for multiple linked graphs;

8. **node-link diagram vs. non-standard representations**, e.g., whether a standard node-link diagram (with certain constraints such as grid drawings etc.) is to be drawn or alternative representations such as matrices, treemaps, or hybrid layouts;

9. **static vs. interactive layout**, e.g., whether the layout is fixed or users can explore and modify it;

10. **2D layout vs. immersive or 3D layout**, e.g., whether the output medium is screen/paper or a large-scale VR display;

11. **classic graphs vs. hypergraphs**, e.g., whether the relational data is modeled as a graph with bilateral relationships or as a hypergraph with multilateral relationships;

12. **full vs. incomplete information**, e.g., whether the entire data is known or whether some data are missing or subject to uncertainty;

13. **general purpose vs. application-specific layout**, e.g., standard algorithms for arbitrary graphs vs. individually tailored solutions for a certain domain;

14. **classic algorithms vs. heuristics/machine learning**, e.g., whether the focus is on rigorous algorithm design and analysis or on data-driven, empirically validated methods.

The talk concludes with a list of high-level challenges in the field, concerning scalability, new quality measures, algorithmic methods, interaction and dynamics, beyond-X graphs, and explorations between theory and practice.

3 Reports of the Working Groups

In this chapter we have included one short report from each of the working groups. As stated earlier each working group chose a single topic (listed as follows) and in this preliminary report, they have provided a definition of the topic together with a high level description of challenges therein. The first three topics can be thought of as broader themes (present in most aspects of graph drawing and network visualization) whereas the latter three are more specific problem domains.

- Section 3.1, Visual Metaphors.
- Section 3.2, Quality Metrics.
- Section 3.3, Human-Centered Graph Drawing and Network Visualization.
- Section 3.4, Time-Varying Networks.
- Section 3.5, Visual Summaries.
- Section 3.6, Graph-Theoretic Considerations.

3.1 Visual Metaphors

Seokhee Hong[a], **Stephen Kobourov**[b], **Giuseppe Liotta**[c], **Yoshio Okamoto**[d], **and Hsiang-Yun Wu**[e]

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Definition: A *relational data set* is a triple $< \mathcal{O}, \mathcal{R}, \mathcal{A} >$, where $\mathcal{O}$ is set of objects, $\mathcal{R}$ is a set of relationships between objects, and attributes $\mathcal{A}$ associated with objects and relationships. A relational dataset is naturally modeled by a *network*, with nodes representing the objects $\mathcal{O}$ and with edges representing the relationships $\mathcal{R}$ between them. A visual metaphor is a geometric instantiation of the network $\mathcal{N} =< \mathcal{O}, \mathcal{R}, \mathcal{A} >$ that specifies how to represent the objects $\mathcal{O}$, relationships $\mathcal{R}$, and attributes $\mathcal{A}$. The goal is an effective visualization that makes it possible to see the underlying objects and relationships and their associated attributes.

We consider the following visual metaphors: node-link diagrams, adjacency matrices, hybrid representations (e.g., NodeTrix), geometric metaphors (e.g., contact and intersection representations), and augmented node-link diagrams (e.g., LineSets, simultaneous embeddings). For each visual metaphor, there are several common associated challenges.

Goal: The main challenge is to design and build effective visual metaphors, i.e., geometric instantiations of a networks defined by objects, relationships and their associated attributes, that make it possible to understand the underlying relational data set.

Organization: We consider 5 research direction across 5 visual metaphors for a total of 25 challenges associated with the pair (research direction, visual metaphor).

Challenges: The selected challenges along this topic rely on the intersection between 5 research direction across 5 visual metaphors. The selected research direction in our discussion includes (D1) geometric space, (D2) optimization goals, (D3) algorithms, (D4) user studies, and (D5) multi-level visualization. Similarly, our selected visual metaphors consist of (V1) node-link diagram, (V2) augmented node-link diagram, (V3) adjacent matrix, (V4) hybrid approach, and (V5) geometric metaphors. The reader can refer to Table 1 for an overview of the selected challenges in the discussion.

	D1: Geom.	D2: Opt.	D3: Alg.	D4: User	D5: Multi-Level
V1: Node-Link Diagram	C1.1	C1.2	C1.3	C1.4	C1.5
V2: Augmented Node-Link Diagram	C2.1	C2.2	C2.3	C2.4	C2.5
V3: Adjacency Matrix	C3.1	C3.2	C3.3	C3.4	C3.5
V4: Hybrid	C4.1	C4.2	C4.3	C4.4	C4.5
V5: Geometric	C5.1	C5.2	C5.3	C5.4	C5.5

Table 1: The 5 by 5 matrix that describes the selected challenges.

3.2 Quality Metrics

Michael A. Bekos[a], Peter Eades[b], Karsten Klein[c], and Tamara Mchedlidze[d]

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The group "Quality Metrics" discussed concepts for quality assessment and quantification for graph visualizations, mostly keeping in mind the node-link diagram metaphor. However, our discussions easily extend to other metaphors that involve placement of geometric shapes such as visibility or contact representations. A quality measure, sometimes also referred to as quality metric, is a classical attempt to quantify the quality of a network visualization in a single number. It can be seen as a function that takes as input a network visualization and outputs a number between zero and one. The higher the number, the higher is the quality of the visualization. Even though this definition sounds simple, it encapsulates a fuzzy notion of quality, which is related to multiple aspects. In most of the research on Network Visualization, quality of a network visualization refers to an intuitive and sometimes subjective mixture of readability and aesthetic value, without being explicitly discussed or defined. In empirical graph drawing research, the quality of network visualizations was mainly studied by measuring the accuracy and speed in task performance (see [YAD$^+$18] for an overview) and by recording the users' subjective preference [PAC02, HHE06, PHNK12]. In our discussions, we identified four general aspects of quality that could be measured by a quality metric. They include, but are possibly not limited to, readability, aesthetic value, engagement and faithfulness of a visualization, with the first three being human-centered and the last referring to the extent to which data is captured by a visualization.

With the goal to better capture the reality of information visualization, where both context (application domain, user experience, tasks to be performed) and device (mobile vs wall-sized displays) play significant role on the actual quality of network visualization, we define the notion of quality metric as follows:

Definition 1 *A quality metric is a function defined in a context for a particular device that takes as a parameter a pair containing a graph G and a drawing $D(G)$ and returns a value (or a vector in multi-dimensional space) that captures one or multiple aspects of the quality of $D(G)$.*

By setting the input of a quality metric to be both a graph and its drawing, we allow quality metric not only to capture the human-centered aspects, but also to reflect on the extent to which the visualization represents the given graph structure, e.g., the faithfulness of the visualization. By allowing the output of a quality metric to be a vector in a multi-dimensional space, we implicitly allow for some visualizations of a network to have non-comparable quality, i.e., to shift from simple optimality to pareto optimality. We have also discussed a weaker definition of quality metric, that for each two visualizations only specifies whether one is superior than the other, e.g., it provides a partial order on the space of visualizations.

The vagueness of the notion of quality itself, and the widened scope of quality metric yielded the following challenges oriented towards defining more truthful quality metrics and their optimization:

- Identification of low-level features in visualizations that predict quality, with relation to research in cognitive psychology
- Formulation of quality metrics based on low-level features, including the understanding of the relationships and dependencies between the features
- Generation and collection of graph visualization benchmarks that could be used to formulate more accurate quality metrics
- Understanding how the specific aspects of the context influence the formation of a quality metric The potential increase in the complexity of quality metrics makes the computational aspects even more challenging

These and other challenges for quality metrics will be outlined in more detail in the full version of this report.

3.3 Human-Centered Graph Drawing and Network Visualization

Daniel Archambault[a] **Andreas Kerren**[b] **Philipp Kindermann**[c] **Kazuyo Mizuno**[d] **Martin Nöllenburg**[e] **and Ken Wakita**[f]

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In graph drawing and network visualization, the final visual representation is always meant to be used by a human user. Therefore, in addition to technological considerations, we must consider how the human, their tasks, their data, and their devices have changed over the years. During the seminar, we identified broad challenges considering advancements in data acquisition, the rise of intelligent systems, human-centered technologies and devices, increasing data complexity, changing user roles, societal adoption of network visualization methods, and visualization literacy. Four broad areas were identified: New Users and New Tasks, Visualizing Big Graphs and Big Data, New Human-Centered Approaches to Quality Metrics, and Human-Centered Layout Creation and Adaption.

Given these areas, we identify example problems that could be of interest to our community over the next decade. However, before describing these problems, we would need to clarify two parts of our perspective.

Changes to the Human in the Loop. In the next decade, due to the scale of the network data sets that a human will need to understand, the traditional human-in-the-loop perspective will need to change. The human-data interaction can start in two ways: the human providing further information on his/her task and automatic analytics or machine learning to summarize data and present it to the user. These two processes will need to work together in order to achieve effective comprehension of large networks as we will not be able to visualize them directly. A second important change is the rise of the crowd and collaborative work as users now can share, create derivatives, and work together on network visualizations and data analytics.

Metrics are User Driven. The metrics for the quality of the visual representation will change. However these new metrics are formalised (engagement, metrics for network explanation, metrics for trust etc.), they should be defined based on the results of user-centered experimentation.

Challenges

We have identified a number of broad areas where the community and its expectations have changed, and will continue to change, with a few example questions to provide some intuition as to what we mean by each.

New Users and New Tasks. The tasks of the user and the users themselves are evolving. In the age of data science, explanation and trust in the visualization of large data sets have become far more important. Exploration is still important, but we will need to invest more fundamental research into visualization methods for network explanation in parallel with the work in the explainable AI community. For example, while animation is not very effective for network exploration, it may be more effective for network explanation, and we will need to revisit visualization techniques in the light of explanatory tasks. Users become more visualization literate, but care much more about the data than the representation (e.g., a Game of Thrones fan is much more interested in geeking out over his/her favorite TV show than in the visualization technology). We also need to better understand how trust impacts user tasks, especially as network visualizations cannot show the entire network as the data sets have become too large. We need to find novel ways of fostering user trust in our analysis and visualizations.

Visualizing Big Graphs and Big Data. Over the past 20 years, the visualization and graph drawing communities have struggled to define what is meant by large graphs. In the next ten years, to be able to answer the questions posed by our new users and tasks, we need to become more formal on what it means to be a large graph and progressive visualization techniques will need to be leveraged to attain this goal. Currently, all techniques to understand a large graph basically turn the large graph into one or more representative small graphs for visualization. Are there techniques out there outside filtering and aggregation that are able to effectively visualize large graphs? Provenance of data and interactions on the data becomes far more important as we cannot show all data elements at once to the user. Cognitive offloading of information to the visual representation becomes far more important as the user cannot remember everything. Can the crowd be leveraged to understand features in large networks? We need to more precisely define what it means to be a large graph and explore effective ways of dealing with them.

New Human-Centered Approaches to Quality Metrics. Many of the metrics behind graph readability have been explored and understood over the past 20 years. However, with the advent of new devices, we are starting to look more closely at other human-centered aspects. Can voice recognition, heart-rate monitoring, brain activity monitoring, and other novel sensors be effectively used to understand the effectiveness of network visualizations? Measuring engagement and emotion involved in the visualization process probably needs to be understood to make the next generation of effective network visualizations. We should leverage this new technology to produce quality metrics that can measure other facets of human-network interaction.

Human-Centered Layout Creation and Adaption. Over the past decade, the concept of the mental map has encouraged the notion of drawing stability: small changes in the network (due to dynamics or interaction) should produce small changes to the layout. Can we produce more formal ways of allowing users to apply constraints to a network and realize those constraints when interacting with it? Can layouts adapt and learn from user interactions to do the right thing given previous interactions? Do we have a chance to create a *one click layout* where the data is automatically analyzed and does the right thing given past feedback from users? Not only will we be trying to create effective methods for network representation, but we will need to take into account past user interactions.

3.4 Time-Varying Networks

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Time-varying network visualization is concerned with depicting and navigating networks that change over time. In this context, networks are graphs with vertex (node) and edge (link) attributes and the changes may involve both the graph and its attributes. Depicting involves the computation of a geometric representation of the network and the computation of its rendering. Navigating involves interacting with the resulting visualization in order to identify features of interest.

Available data, in terms of changes in the graph or in its attributes, can have the following features: They can be fully known in advance (off-line scenario) or not (on-line scenario) They can have different frequencies They can exhibit a periodic behaviour They may occur at specific time instants or within time intervals In a certain time instant (or time interval) one or more changes can occur Time can be encoded in to the graph (e.g., phylogenetic trees) The structure of the graph and the value of the attributes can be either known in all the possible instants (hypothesis of continuous time) or only in specific instants (hypothesis of discrete time).

Design Considerations

Extending the classification in the taxonomy of Beck et al. [BBDW17], time-varying network visualization requires at least the following main choices:

1. Visualization metaphor for the network structure including interaction techniques: node-link representations, intersection graphs of geometric objects (e.g., for exploration and storyline visualization), matrix-based representations, hybrid visualizations.

2. Visualization metaphor for the network attributes including interaction techniques: labels, colors, size, some other superimposed semantics, etc.

3. Representation of time: time is mapped to time (time-to-time mapping) or time is mapped to space (time-to-space mapping)

4. Mental map preservation: the user should not be disoriented by network changes (this is somehow correlated with drawing stability)

5. Modeling of transition: transitions can be emphasized in several ways (e.g., with morphing techniques).

6. Time-based filtering: only the portion of the network induced by the last k changes is displayed (for some k) (e.g., sliding windows in a streaming model).

Challenges

Based on the above design considerations we have identified the following main challenges, each of which gives rise to specific challenges in terms of designing visualization systems for time-varying networks and in algorithmically computing such visualizations:

- Effective mapping of time
- Trade-off between drawing stability and drawing aesthetics
- Visual exploratory analysis of commonalities and differences of networks evolving over time
- Visual exploratory analysis of large time-scale networks
- Effective visualization of evolving clusters

3.5 Visual Summaries

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Visual summaries provide a *succinct* and *faithful* visual abstraction of graphs and networks. Such visual summaries serve to aid human comprehension of complex data and help to overcome the limitations posed by screen sizes and computational power. We focus on visual summaries of geometric graphs, possibly with additional attributes, such as labels or weights associated with vertices and edges.

A *visual summary* of a geometric graph $G = (V, E)$ is a succinct and faithful visual representation of G of low visual complexity. Visual summaries can take many different forms: for example, representations via matrices or linearizations, schematic drawings, possibly using glyphs, of either G or its statistics, or simply a geometric graph with possibly additional attributes. In this section we consider the latter type of visual summaries, which we refer to as *generalizations of geometric graphs*. A generalization of G is a geometric graph $G^\circ = (V^\circ, E^\circ)$ of reduced complexity which captures the essential properties of G while being easily comprehensible for a human viewer. Such a generalization might have additional attributes associated with its edges and vertices. Refer to Figure 1 for an illustration.

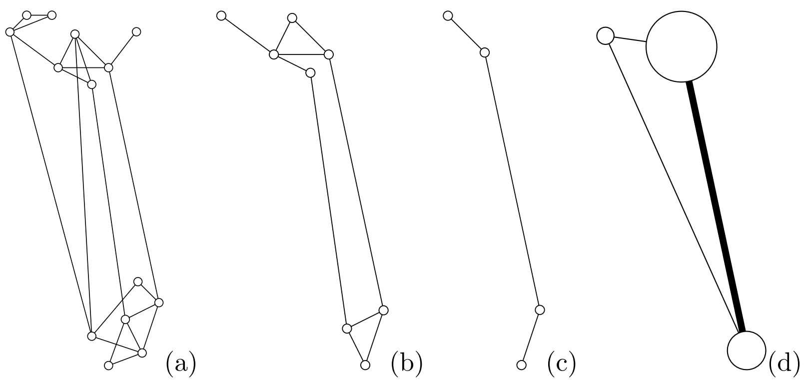

Figure 1: (a) A geometric graph. (b) A generalization of it. (c) A more succinct generalization. (d) A generalization that exploits different sizes for nodes and edges.

Some representative challenges for generalizations are as follows.

Challenge 1 What are essential properties of a geometric graph G and how can they be captured by metrics for provable faithfulness of a generalization G° of G?

Challenge 2 Should a generalization contain new vertices and edges or should it be a subgraph of the input graph? Which of the two models is better and in which context?

Challenge 3 Given some quality metrics, how can we efficiently compute generalizations or even (continuous) hierarchies of generalizations (based on some scale parameter) with provable quality guarantees?

3.6 Graph-Theoretic Considerations

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Topological and geometric graph theory is the study of elegant graph-theoretic concepts related to graph visualizations. The theoretical questions motivated by and relevant for Graph Drawing and Network Visualization include algorithmic challenges, questions of complexity, as well as structural investigations.

In fact, many concepts such as planar graphs [NC88] and interval graphs [Fis85] were considered before from a purely theoretical point of view and became crucial in Graph Drawing later [Tam13], e.g., through constrained embedding problems and the use of PQ-trees therein. On the other hand, Schnyder woods were introduced for the purpose of drawing planar graphs efficiently on a small grid [Sch90] and evolved into one of the most versatile techniques for understanding planar structures in theory. To summarize, there is a feedback loop: Graph theory inspires graph drawing and vice versa.

Today many important questions require a combination of algorithmic and structural investigations together with geometric considerations. In the following we list some challenges in the interplay between graph theory and visualization. Progress on them would constitute major advances in both fields. The list below is not intended to be comprehensive, it includes useful generalizations of planarity, more versatile algebraic techniques, a better understanding of representation problems, a parametrized view on intersection representations, and closing the feedback loop with applicability of geometric representations for visualization.

Useful Generalizations of Planarity While many mathematically interesting generalizations of planarity have been introduced [DLM19] they often come with the pitfalls of lacking the elegant (and practical) algorithms and "nice" drawings that come with planarity.

More Versatile Algebraic Techniques This challenge concerns the development of methods, tools, and theory for handling algebraic geometric properties of graph drawings, such as edge lengths, face areas, edge slopes, or angles.

A Better Understanding of Representation Problems In the basic recognition/construction problem one is given an abstract graph and a desired "type" of representation, e.g., planar drawing, interval model, etc. This was recently generalized to the partial representation extension and simultaneous representation versions where one is either given a part of the desired representation required to be in the output, or one is given several graphs with labelled common subgraphs the goal it to produce a representation of each graph where the representations agree on the common subgraphs. The challenge here is to understand when these generalizations are harder than the classic problem and to clarify the relationship between these problems.

A Parameterized View of Intersection Representations While basic geometric graph classes such as interval graphs are well understood and lead to elegant theory and efficient algorithms, such classes only allow for quite special graphs. Moreover, while several attempts have been made to generalize the "nice" properties of interval graphs in a parameterized way, these often quickly lead to intractability in computing the obtained parameter [CTVZ17]. The challenge is how to find such parameterized intersection representation, e.g., this could provide a useful parameterization of dense graphs.

Applicability of Geometric Representations for Visualization With the wealth of understanding of geometric graph classes, there seems to still be a lack of understanding how one can translate these representations back into the world of graph visualization. The challenge here is to understand what makes a geometric representation viable as a visualization (e.g., does it make sense to use interval models?).

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