SITUATING VISUAL NETWORK ANALYSIS

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ABSTRACT (ENGLISH)

Visual network analysis (VNA) is the practice of analyzing networks by visual means. In this dissertation, I account for this practice and the techniques involved by focusing on force-directed node placement algorithms, the most popular strategy for drawing network maps. I explore the question of what we see when we look at networks, address some of the criticism faced by network visualization, and reflect on the role of the layout algorithm in the visual mediation of the network's topological structure. My argument unfolds in six theses: (1) VNA consists of practices that are only partially determined by the graph-drawing and data-visualization literature; (2) some visualizations, including network maps, prompt a visual inquiry into the meaning of emergent patterns as contributing to their apparent self-evidence; (3) for historical reasons, the graph-drawing literature mainly promotes an interpretation regime adapted to small networks (*diagrammatic*), while practices partially shifted in the 2000s to large networks (*topological* interpretation regime); (4) some issues with reading network maps can be attributed to the misalignment between our visual cognition and the computational standpoint, notably the notion of the group; (5) the existing justifications of algorithm designers do not provide a compelling explanation of what we see in networks; and (6) the literature on *community detection* focuses on clear-cut clusters, while force-driven placement algorithms make visible other non-clear-cut community structures.

ABSTRACT (DANISH)

Visuel netværksanalyse (VNA) er en praksis, der har udviklet sig omkring analysen af netværk med visuelle midler. I denne afhandling redegør jeg for denne praksis og de involverede teknikker ved at fokusere på den algoritmiske placering af noder ved hjælp af kraftvektorer, den mest populære strategi til tegning af netværkskort. Jeg undersøger spørgsmålet om, hvad vi ser, når vi ser på netværk, adresserer den kritik, som netværksvisualisering ofte er genstand for, og reflekterer over layoutalgoritmens rolle i den visuelle formidling af netværkets topologiske struktur. Mit argument udfolder sig omkring seks hypoteser: (1) VNA er en praksis, der kun delvist bestemmes af graftegnings- og datavisualiseringslitteraturen; (2) nogle visualiseringer, herunder netværkskort, lægger op til en undersøgelse af betydningen af mønstre på en måde, der bidrager til deres tilsyneladende selvindlysendehed; (3) af historiske årsager fremmer graftegningslitteraturen hovedsageligt et fortolkningsregime tilpasset til små netværk (*diagrammatisk*), mens praksis delvist skiftede i 2000'erne til store netværk (*topologisk* fortolkningsregime); (4) nogle problemer med læsning af netværkskort kan tilskrives forskellen mellem vores visuelle erkendelse og det computationelle udgangspunkt, især omkring begrebet gruppe; (5) algoritmedesigneres eksisterende begrundelser giver ikke en overbevisende forklaring på, hvad vi ser i netværk; og (6) litteraturen om detektion af grupper fokuserer på klare klynger, mens kraftdrevne placeringsalgoritmer synliggør andre, mindre klare gruppestrukturer.

ACKNOWLEDGEMENTS

Let me start with a tribute to my teacher and friend Franck Ghitalla, who sadly passed away in 2018 while doing what he loved: teaching knowledge cartography. He sparked my interest in networks when I was a student, and it remained with me ever since.

Following my initial effort, Mathieu Bastian, Sébastien Heymann, and Eduardo Ramos Ibáñez have supported most of the burden of the Gephi project. Gephi would not exist today without them. They have also contributed to the Gephi papers included in this dissertation.

I owe my interest in sociology to Dana Diminescu, with whom we studied the web of migrants. I would never have had the confidence to step out of engineering without the intellectual home she provided me with.

Bruno Latour and Tommaso Venturini taught me how to write. I am grateful that the Sciences Po médialab (notably Guillaume Plique, Paul Girard, and Benjamin Ooghe Tabanou) allowed me to spend time writing instead of developing tools, supporting my ever-changing engagement with science.

My double migration from France to Denmark and from engineering to research was only possible because Anders Munk assured the material and intellectual ground. He bridged the médialab with the TANT Lab, mentored the construction of my research project, and naturally became my supervisor. The entire TANT Lab and notably Anders Koed Madsen (my co-supervisor) and Torben Elgaard Jensen welcomed me and expanded my STS horizons.

Of course, this adventure would never have been possible without the unwavering support of my partner Noémi Schneider. I can only underestimate how my ability to face change draws on the strength and stability she brings me—and to be fair, our two cats.

I see collaboration as a joy of research. Tommaso Venturini and I have often joined our efforts in writing. In one of the papers included in this dissertation, Liliana Bounegru and Jonathan Gray helped us engage with network practices in data journalism. In another of the papers included, Pablo Jensen offered Tommaso and I his mathematical skills and intuitions. In yet another, Emilija

Jokubauskaitė accepted that we rediscuss her empirical study of practices with Gephi, where I learned a great deal. I also had the chance to draw on the experience of Martin Grandjean, an excellent digital humanist and inspirational Gephi expert.

To all of you, with whom this work is entangled, please accept my most heartfelt thanks.

Finally, I also want to thank a certain Wuhan bat, who sadly finished in a soup, for encouraging me to spend months locked down at home, writing away.

NOTE ABOUT MY RESEARCH BLOG

I self-publish parts of my work on my research blog *Reticular*[1]. In some cases, I simply share information that I consider useful, for instance as teaching material. In other cases, I publish quickly written essays where I unfold ideas at an early stage of reflection. My research blog plays a similar role as a notebook, except it is public and digital. My research process occasionally draws on this pool of ideas to bootstrap slides or publication drafts. In the same spirit, parts of this dissertation are also related to some of my self-published posts.

Two sections are reworked versions of blog posts: "Interpreting networks visually is a challenge" and "The noema of big data visualization". Two other sections have been republished on the blog as teaching material with minor modifications after they were written for the dissertation: "Network analysis and other fields concerned with networks" and "Gestalt, clusters, and hairballs: eye-topology misalignment." I will indicate the related blog posts when relevant place as footnotes.

1 *https://reticular.hypotheses.org*

TABLE OF CONTENTS

PREFACE

My interest in networks was passed on to me by one of my teachers, Franck Ghitalla, who had just read Albert-László Barabási's bestseller *Linked*. Like many others, I was intrigued by the discovery of the scale-free network, a new and exotic structure that scientists began finding in every aspect of the world, from genetics to economy, the power grid to terrorism, and to love—at least, this is what Barabási claimed.

With Ghitalla and other engineering students, we developed an apparatus to visualize the shape of the web (Ghitalla et al., 2004). Our goal was to explore, and we conceptualized our endeavor as *information geography*. The web was a natural playground for a group of challenge-hungry engineers-to-be, but Ghitalla's angle was not typical of an engineering school. He was a linguist, and for him, the web was not data; it was knowledge. He shared with us a double interest in graph theory and visualization while also highlighting innovative ways to account for digital information. First, he introduced us to the nascent field of network science. Around the same time of the emergence of Google, Barabási and Réka Albert were trying to measure topological features of the web (Albert et al., 1999). Like them, we wanted to explore the web as a space. Second, Ghitalla shared his interest in the area of information visualization, specifically in relation to Martin Dodge's *An Atlas of Cyberspaces* (see Figure 1; Kitchin and Dodge, 2001). Our interest was in measuring and visualizing: our perspective was to account for the structure of information as an empirical phenomenon.

Later, I joined the group of Dana Diminescu, a sociologist who had conceptualized the "connected migrant" (Diminescu, 2008). For her, the migrant was not uprooted; the migrant was capable of maintaining links (and control), at a distance, from their destination country to their country of origin. She knew that migrants were pioneers of information technologies, and she wanted to complement her fieldwork by investigating the web, despite facing major technical issues. At the time, circa 2008, the tools capable of mining the web and visualizing networks required specific expertise in computer science. My role, as an engineer, was to provide her and her colleagues with the operational means to investigate the web. Together, we built the e-Diasporas Atlas project (Diminescu et al.,

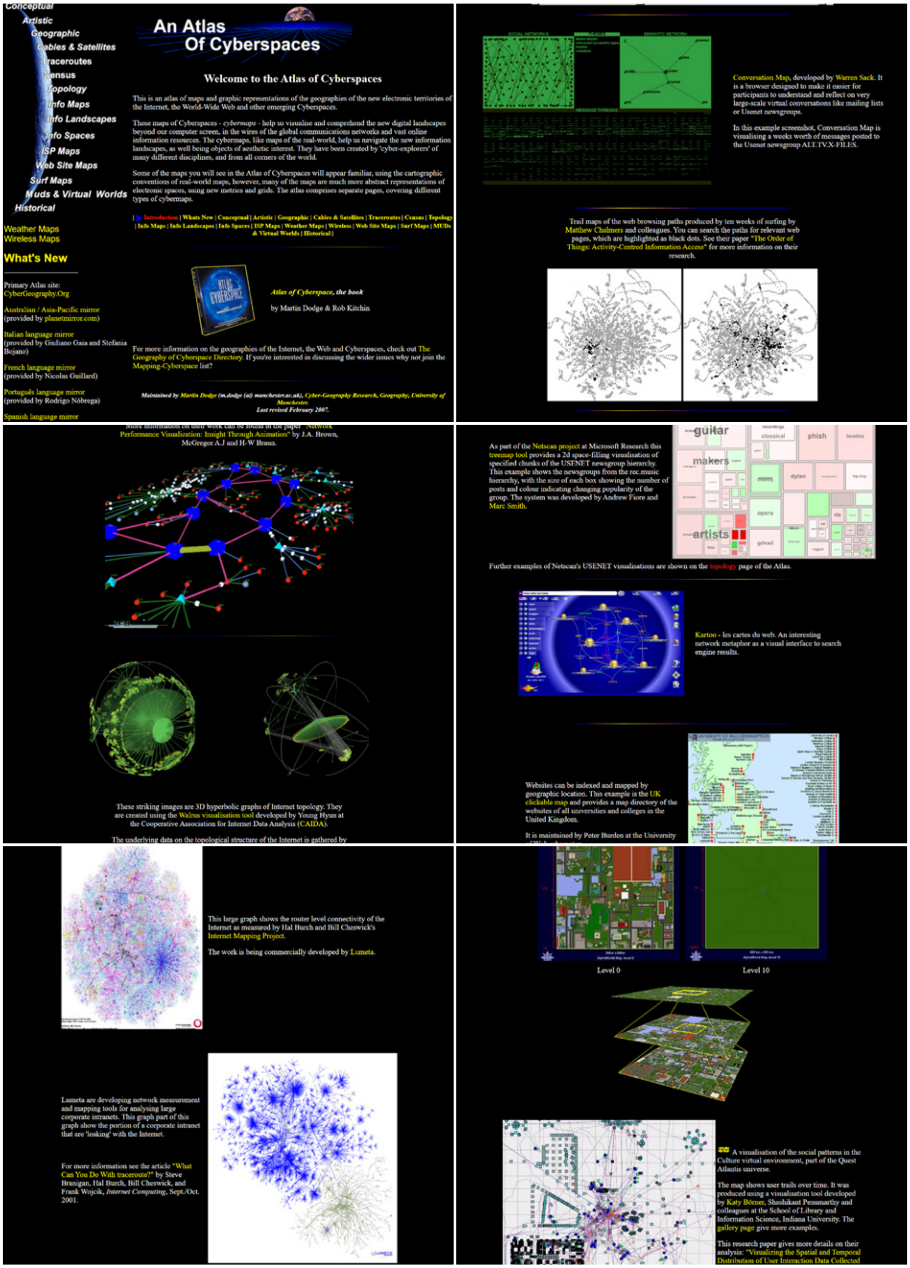

Figure 1. Screenshots of Martin Dodge's "An Atlas of Cyberspaces," the website of the cybergeography research project, active from 1997 to 2004. © Martin Dodge, 2007. This work is licensed under a Creative Commons License.

2012), a collaborative exploration of the web of diasporas (on the apparatus, see Diminescu et al., 2011; on the project, see Diminescu, 2012).

We were inspired by "Divided They Blog," a seminal paper by Adamic and Glance (2005), which accounted for the extreme political polarization of the US blogosphere. This paper featured a picture whose importance appears in this dissertation, reproduced in Figure 2. It inspired us for two reasons: the network was unusually *large* (in our eyes), and we saw *clusters*. It was a moment in which the research community was discussing *data deluge*, the idea that sufficiently large amounts of data could speak for themselves, an idea voiced by the editor-in-chief of *Wired*, Chris Anderson (2008), in his famous editorial "The End of Theory." For Anderson, we could "analyze the data without hypotheses about what it might show." Data visualization had entered a different era. Thus, the joyful visual exploration showcased by Dodge was replaced by the operational goal of making specific patterns visible. "Information" started sounding less like "knowledge" and more like "data." We hypothesized that the web of migrants had, to some extent, a community structure. We wanted to study it, and as such, we wanted to *see* it.

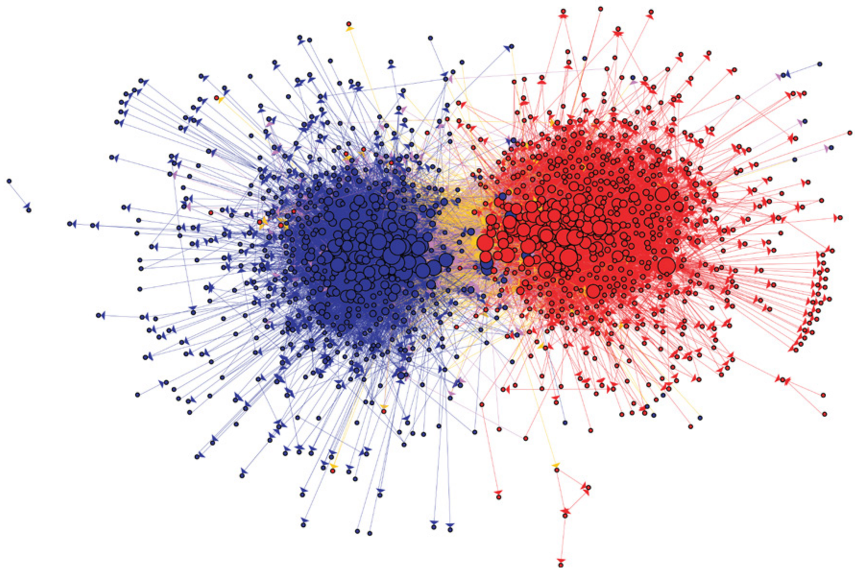

Figure 2. The political blogosphere plotted in "Divided They Blog" by Lada Adamic and Natalie Glance, using Eytan Adar's instrument GUESS. Credit: Adamic and Glance (2005): Figure 1.

First, we used the instrument GUESS, which was developed by Adar (2006) and used by Adamic and Glance (2005) to produce the image shown in Figure 2. This entailed frustrating limitations, and I decided to try to make a better one. I developed a prototype (Figure 3(a) and (b)), which was promising, but I did not have the skills to transform it into a full-fledged application. We enrolled other engineers into our informal project. Mathieu Bastian became the lead developer, and Sébastien Heymann took charge of community management. I assumed the role of designer while also working on algorithms. We named the tool Gephi (Figure 3(c) and (d)). We created a website, published tutorials, and showcased it in academic conferences (Bastian et al., 2009). The e-Diasporas Atlas project was a fruitful testbed for this instrument. I spent time with each scholar involved, ensuring that they could use Gephi without my assistance. The tool was largely shaped by these interactions and evolved to meet the expectations of the social science scholars and digital humanists contributing to the e-Diasporas Atlas project.

Gephi was successful. At the time of writing, it had been downloaded millions of times during its decade of existence. We presented a poster at the ICWSM conference (Bastian et al., 2009), which became Gephi's proxy paper and has been cited thousands of times. A paper on a layout algorithm I had developed for Gephi, "Force Atlas 2" (Jacomy et al., 2014), has been cited hundreds of times. A community emerged around Gephi, and people I had never heard of started teaching it, producing tutorials, and developing plugins. They became Gephi experts, answering the questions of beginners on social media, sharing their own perspective on the tool, and using it in unexpected ways. These were some of the signs prompting me to write that Gephi was, indeed, successful. Bastian, Heymann, and I benefited from Gephi's symbolic capital. It offered us opportunities. I was hired at the Sciences Po médialab, a hybrid laboratory founded by Bruno Latour, to contribute to the apparatus of digital methods and controversy mapping. Success brought us opportunities, but it also had other consequences.

Success amplified everything and highlighted things that would have otherwise gone unnoticed. It gave weight to Gephi's design: the good decisions, the bad ones, and what we decided without realizing it. It gave importance to contingencies such as accidents, biases, and bugs. Gephi has received a healthy dose of criticism, despite being generally appreciated by its users. Some critics point to flaws that I also regretted, such as the lack of an "undo" feature, a known yet difficult-to-fix problem. Some consider Gephi a black box, despite my efforts

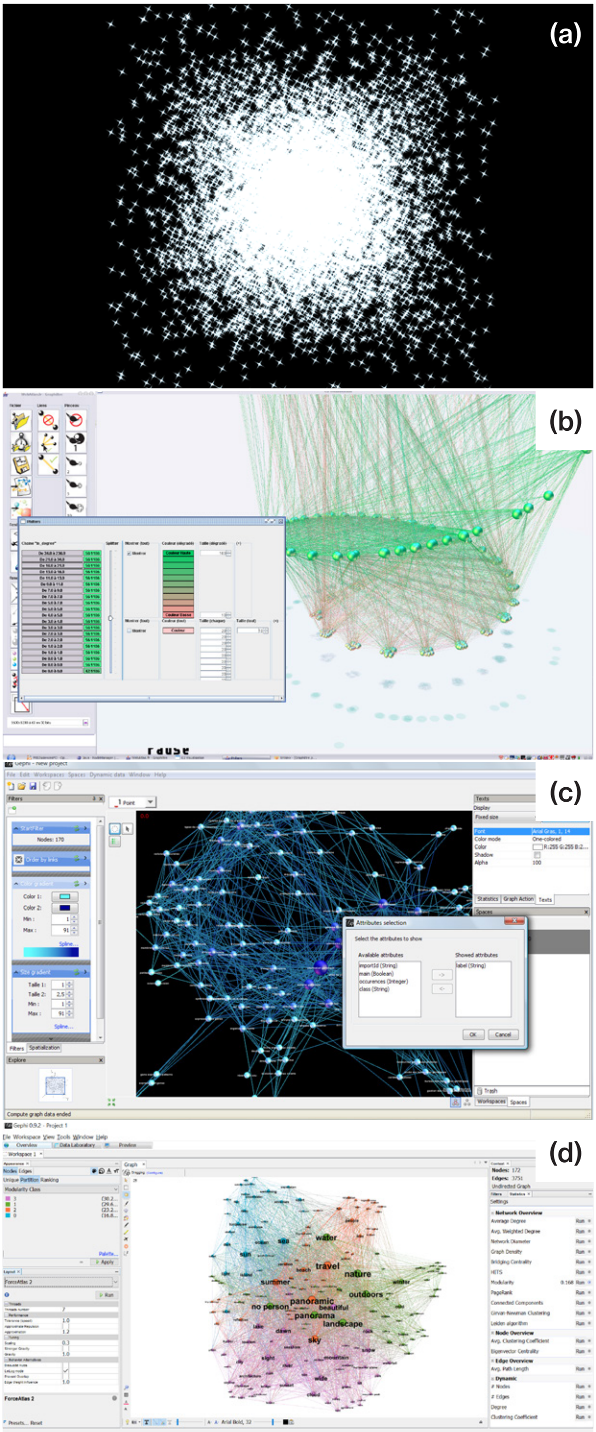

Figure 3. Screenshots of Gephi over the years: (a) proof-of-concept, 2006, a visualization engine using the GPU and a node placement algorithm; (b) prototype named "Graphiltre," 2007, featuring a graphical user interface (GUI) for manipulating the view and filtering the network; (c) Gephi in 2009, featuring the statistics module, graph layers, and a single window GUI; (d) Gephi in 2018; the layers and some features have been removed and new features added.

at avoiding this. I listen to this criticism in order to improve Gephi, and what I hear surprises me. I realize two things. First, users assume that every aspect of Gephi's design has been decided for a reason. This is not the case, as we were not strategizing a product; rather, we were tinkering a device. Second, users incorrectly assume that what Gephi performs can always be adjusted by intervening in the design. Of course, a different design has different effects; but which ones? What a different design would entail remains difficult or impossible to anticipate. This is largely an effect of success. I hope to explain this with a metaphor: a large number of users are like a river: it flows down its own direction, and given enough time, it shapes its environment. It interacts with itself, spawning unpredictable perturbations. It has a life of its own and a rhythm of change (Figure 4). A tool acts like a rock attached to the bottom of this river. It diverts the stream and impacts erosion by changing where sediments flow and deposit, indirectly shaping the riverbed. The rock matters, yes. However, the actual force of change is the water flow. On its own, the rock changes nothing. One cannot guess how the river will change just by looking at the rock because it depends on the nature and direction of the flow. The community of Gephi users has understood the tool in its own way, shaping its own practices, and framing Gephi in ways that I had not anticipated. This situation is not unusual, but it has had an unexpected consequence for me as a tool maker. Criticism does not tell me where to intervene in order to improve Gephi. The greater the success, the more difficult it is to shape the practices through design intervention.

I believe that Gephi was successful because it was convenient, not because it was scientifically relevant. I am not saying that it was not relevant! I did (and do) believe in Gephi's usefulness to scholars, even though I cannot prove it. This is a major point of this dissertation. We did not need evidence or justification. Gephi was convincing by itself because it was sufficiently efficient and convenient, not because it was implementing a better method than other devices. We did not willingly implement a method; we only focused on making a device that was convenient to use. Now, there is a point to argue that Gephi implements a method, but let us agree that, in this case, the method did not predate the instrument. It is important to wonder about the method—an important question for users because they want to know what they are doing with Gephi. Nevertheless, I do not possess the answer, which is the surprising condition of tool-making. Even though, in some sense, I made Gephi, I cannot tell users what the instrument performs. I prefer admitting this than pretending that I own and control my creation. Gephi has a life of its own, and making it did not require assessing

Figure 4. The unpredictable shapes emerging from the interaction between river flows and the land. High-altitude oblique aerial photograph looking south toward the junction of the Yukon and Koyukuk Rivers (Pewe, 1975). Alaska, August 1941. Public domain.

its epistemological commitments, a task that would require skills other than software engineering and interaction design. Discovering what Gephi performs requires a different effort from making it, which is what I endeavor to tackle in this dissertation.

My starting point is the faith that it is possible to interpret networks visually. The impression is that, at least for me, it worked. A decade spent engaging with networks has helped me build expertise in how to understand them. I do have biases, but as I have in-depth knowledge of how layout algorithms work, I am not misled by a lack of awareness of the mediations involved. I have a precise idea of what I can and cannot trust, which structures are manifested by certain visual patterns, and which structures are not manifested by a visualization. Thus, I *know* how to interpret networks. Nevertheless, this knowledge is empirical; it consists of an expertise based on my own experience. Leveraging this internalized knowledge to answer the question of Gephi's method requires two important steps: first, externalizing it, writing it down and, second, assessing it. It requires grounding what makes the visual interpretation of a network valid. The most difficult step is, of course, the second one. Indeed, there is not just one ground but many, and not all are equally solid.

I addressed the first step, documenting how to read networks, at the Sciences Po médialab. Tommaso Venturini helped me format this knowledge into teaching material and academic publications (Venturini et al., 2014), and we settled on the name of visual network analysis (VNA). During this process, I gradually engaged with the social science and humanities literature on networks, and I engaged with network analysis beyond the case of Gephi. I realized three things. First, the lack of justification for VNA prevented scholars from contextualizing their practice, either in their publications or for themselves. As an engineer, I had not considered the situation from that angle. Second, the question was poorly discussed in the existing literature. The information design literature did not address the specificity of networks, while computer science research, including graph drawing, rarely addressed matters relating to semiotics or hermeneutics. The academic literature debated the community structure of networks, what it meant, how to detect it, compute it, and even visualize it. However, it did not debate the hermeneutic dimension of visualization: what do we see when we look at a cluster? I tried to find an answer, then came my third realization: this problem was difficult. It required more than compiling existing works in different fields; there was a lack of knowledge on the specific issue of interpreting large networks visually.

I made Gephi out of curiosity because I wanted to see and understand for myself. The tool was a byproduct of this personal exploration endeavor. To this day, I am still perplexed by networks. Their resistance to understanding lasted much longer than I had anticipated. There is something truly alien in them, a sentiment that persisted even after networks felt familiar to me. In our struggle to understand networks, I saw a prefiguration of future challenges on complexity. When I looked at scholars' network practices, I saw the solutions we invent when we face something that we are not equipped to apprehend. How we face this unyielding resistance to understanding interested me. I wanted to go down the rabbit hole and explore this question. I decided to engage further with academic life by writing a Ph.D. thesis, and understanding networks naturally became the topic of my research.

Can we know networks by looking at them? How? And if so, why does this knowing work, where does it fail, and where does it shine? To give you an idea of what I try to accomplish, take a look again at Adamic and Glance's (2005) red and blue clusters (Figure 2). We see two groups of dots; this is a fact. The Democrat blogs (blue) gather on one side, while the Republican blogs (red) gather on the other side: true. At which point do you get to know about the structure of the network? *Statistics* tell us that these two groups do not cite each other much; this is a fact. Adamic and Glance do not pretend anything else. How, therefore, do we conclude that the visual clustering of the dots *means* that the groups are poorly connected? Spending time with Gephi gives you the certainty that community structures produce visual clustering, but trust is not a justification. Understanding the picture requires knowing how the nodes are placed. This involves an algorithm. Can we not know this algorithm? We know that it *tries* to bring connected nodes closer, but this task is actually impossible, and we know for a fact that it fails for many node pairs. We also know how the algorithm works, but its functioning does not tell us why it produces such outcomes—the same way that gravity does not tell why dropping sand makes a pile. Deep down the rabbit hole, at the intersection of the algorithm and visual cognition, it turns out that we still cannot explain what we see when we look at networks. Seeking an answer led me to write this dissertation.

1. INTRODUCTION

Visual network analysis (VNA) is the practice of analyzing networks by visual means. In a sense, all analyses are visual; even reading a number is visual. However, networks have something that gives a special character to the term "visual." Networks *per se* do not have a shape, in the usual sense of the term. The shape is only produced when, and if, we draw them, which is why we need to place the nodes and edges in the two dimensions of the screen or paper. We need to invent a shape, taking into account the topology of the network. We can craft that shape manually, but for large networks, we usually delegate the task to an algorithm. The practice is widespread, notably in the social sciences (e.g., Bruns, 2012) and humanities (for an overview, see Grandjean and Jacomy, 2019), although it is rarely situated.

Situated VNA is a reference to Haraway (1988), although I also have my own way of "situating." Haraway warns us about knowledges that pretend to be true independently of the context within which they originated. Such knowledges seem true by the sole virtue of their existence, as their power of conviction lies in their apparent self-evidence rather than their traceability. Nevertheless, they assume the untheorized preexistence of both the knowing subject and what it gets to know. As appealing as a context-free veridiction theory might be, all knowledges depend on how they were produced. In "Situated Knowledges," Haraway (1988) demands nothing more than contextualized truths that we can critically re-examine. Formulated as such, the demand does not seem subversive, yet it plays against dominant forms of scientific knowledge, such as the quantitative procedures offered in predominantly white, male cultures as the pinnacle of objectivity. Haraway's demand for situatedness has roots in feminism, but it does not end there. Statistics are often seen as a gold standard against which other forms of knowledge can be assessed, for instance, an ethnographic account. Here, objectivity refers to independence of context. In comparison, qualitative analyses are considered subjective because they depend on who performed them. In this understanding of objectivity, it is tempting to guarantee truth by mechanical reproducibility because it puts organic inconsistencies, such as human subjectivity, at a distance. Nonetheless, dependencies and attachments are present everywhere, revealing the entanglement of any situation. Even statistics are the fruit of a historical process (Hacking, 2008). The design of technologies that make procedures reproducible perform certain choices. People have decided which research to conduct, which technology to fund, which methodology was publication-worthy, and who was hired. We need to hold knowledges accountable, and therefore, the conditions of their production must be visible and accessible. Unsituated knowledges are not context-free; they only pretend to be.

Network maps are criticized for being insufficiently situated, a point I take seriously. Drucker (2014: 125) writes that visualizations "are a kind of intellectual Trojan horse," while Ruppert and Scheel (2019: 10) see them as "a vehicle … for [the] claimed self-evidence [of the data]." For Rieder and Röhle (2017: 118), network maps lead to a "lack of awareness of the layers of mediation network analysis implies and thus to limited or essentialist readings of the produced outputs that miss its artificial, analytical character." Network maps are too easily understood as context-free, and this lack of situatedness plays in favor of the rhetoric of big data. They are rarely critically re-examined and offer no resistance to instrumentalization. Networks are routinely showcased as demonstrating superior technical skills or mastery over complex phenomena, as asserting the quantification of large data bodies, and more generally as impressing gullible audiences. This is possible only because the situation of network maps is not visible to their publics.

In this dissertation, I endeavor to address this issue, hence the title: *Situating Visual Network Analysis*. However, this operational perspective runs into conceptual difficulty from the start, because *situating* immediately begs the question: for whom? If situatedness is about the relation of the knower to the known, then it is, of necessity, a multiple. Network maps, like most visualizations, are used in multiple contexts, for distinct purposes, and are variously understood by different publics. Situating is not about building a unified theory of VNA but about accounting for different contexts, practices, and standpoints. Despite relatively unified criticism, addressing VNA has multiple facets. The authors quoted in the previous paragraph criticize the *apparent* context-freeness of data visualization because they know better. When they condemn the "lack of awareness of the layers of mediation" involved (Rieder and Röhle, 2017: 118), they speak for others, not for themselves. Situatedness lies in the re-examinable relation of the knowing to the known, and different publics bring different situations. Therefore, situating VNA supposes an array of tasks: describing how network maps are used in different contexts by different publics; inquiring into why certain publics understand

and/or perform them as self-evident; elucidating what makes it difficult or impossible for experts to make visible the layers of mediation involved; and, for me as a tool maker, proposing ways to deviate or counterbalance the problematic effects of network visualization. These steps constitute, roughly speaking, the program of this thesis.

VNA is a practice that precedes a theory. Some scholars presume that they can understand networks by looking at them, but the academic literature provides no way of assessing the validity of their interpretations. Foucault Welles and Meirelles (2015) tell the story of a network pictured in "Divided They Blog," a seminal paper in which Adamic and Glance (2005) study the US political blogosphere (Figure 2). The figure illustrates the methodology, but it is not offered as a piece of evidence (the point is solely argued on the basis of a distinct statistical measure). However, Foucault Welles and Meirelles (2015) point out that other authors present it as such. For instance, Christakis and Fowler (2009) write: "What **immediately stands out** is the extreme separation between liberals and conservatives. … Just like the real-world political networks … the online social network appears to be strongly homophilous and polarized" (2009: 206, emphasis added). There is no doubt that network visualization can be telling, but self-evidence does not equate to scientific validity. In fact, the authors rarely provide justification for their visual interpretations, and this lack is not necessarily considered a scientific problem. As Bruns (2013) notes, "relatively few of the scholarly publications which draw on [the network analysis software Gephi] to visualise the social networks they study insert any substantive discussion of the benefits or limitations of the particular Gephi network visualisation algorithms they have chosen. … Neither, it should be noted, do the referees for articles on these topics usually request such methodological information." Bruns hints at the core issue: interpretations depend on algorithms, making them notoriously difficult to assess. I will progressively establish why the hermeneutic dimension of layout algorithms is poorly theorized. I will retrace the history of graph-drawing algorithms and their evaluation and argue that it boils down to practices leading the way, as the discussion in the academic literature has lagged behind. Let us, for a moment, retain the key element: VNA is first and foremost a practice.

Visual interpretations of networks are poorly situated. I mean here that the conditions of the production of network maps are not always accessible to everyone, sometimes to no one. The reasons are multiple, and I will explore them. I have mentioned that one of the main criticisms of data visualization in the social sciences and humanities takes inspiration from Haraway's (1988) notion of "Situated Knowledges." She criticizes "the god trick of seeing everything from nowhere" (p. 581), and indeed, I observe scholars interpreting networks as if they were self-evident, as if their epistemological commitments were minimal (they are not), praising their (alleged) objectivity. Network maps can produce such an effect and are rightfully criticized for it. Following Haraway, I defend the notion of objectivity based on partiality, based on a re-examinable sensemaking process rather than independence of context. I contend that network maps are not objective because they are uncommitted but, on the contrary, because we can explore their commitments: the methodological choices that are made by the map maker, the tool designer, the algorithm itself… In Haraway's own words, "the only way to find a larger vision is to be somewhere in particular" (p. 590).

These problems may sound abstract, since I have not yet presented what VNA entails in practice. I dedicate the remainder of this introduction to a step-by-step introduction to this matter: an overview of the publications included in this dissertation, a practical example of visual analysis, and a problematization of VNA.

The dissertation is organized in six chapters. The first is the present introduction. Chapter 2 explores VNA from different angles: in the academic literature, as a practice, and from the perspective of its critiques. Chapter 3 focuses on graph drawing. I retrace the history of the discipline and propose a critical state of the art. Chapter 4 explores the hermeneutics of network maps, articulating how we perceive certain patterns through the semiotics of network maps and the mathematics of graph drawing. I will also discuss the justifications offered by algorithm designers to frame the visual affordances they produce. Chapter 5 offers two interventions aimed at improving the practice of VNA, providing meaningful contextual information to network maps. Chapter 6 is a short conclusion.

PAPERS INCLUDED IN THIS DISSERTATION

The papers gathered in this dissertation (provided as appendices) contribute to situating VNA in four ways:

1. By documenting the instruments and algorithms that have made the practice possible;
2. By providing exemplary visual analyses, good practices, and guidelines;
3. By exploring the different understandings of networks;
4. By intervening in the practice of VNA to (try to) improve it.

When I mention one of the papers included in this dissertation, I use its short name in quotation marks, followed by an asterisk, for instance: "Translating Networks."* I omit the reference for brevity, but they appear below.

INITIAL CONTRIBUTIONS TO THE FIELD OF NETWORK ANALYSIS

First, the two oldest papers, "Gephi"* and "Force Atlas 2,"* written with Mathieu Bastian, Sébastien Heymann and Tommaso Venturini, document my initial contributions to the field. The former presents Gephi, an instrument dedicated to (visual) network analysis, which I contributed toward creating, while the latter presents and discusses a layout algorithm that I developed, Force Atlas 2, which is implemented in Gephi.

Gephi (2009)

This two-pager was published in the *Proceedings of the International Conference on Web and Social Media* (ICWSM) 2009.[1] This is generally cited when researchers use Gephi (6,100 times according to Google Scholar, 21 August 2020). It was awarded the Test of Time Award at ICWSM 2019.

Force Atlas 2 (2014)

Published in *PLoS ONE*.[2] It is often cited when researchers use the Force Atlas 2 algorithm (1,300 times according to Google Scholar, 21 August 2020).

EXEMPLARY ANALYSES AND GUIDELINES

The second group of papers proposes exemplary analyses and good practices and discusses the tenets of VNA. In "Visual Network Exploration for Data Journalists,"* Tommaso Venturini, Liliana Bounegru, Jonathan Grey, and I showcase how to use metrics to compensate for the main weakness of network maps: their inability to account for hierarchies in the direction of links. In "What Do We See When We Look at Networks?"* Tommaso Venturini, Pablo Jensen, and I showcase the visual analysis of a large network, what it entails, and how the layout algorithm operates as a mediation.

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1 Bastian, M., Heymann, S. and ***Jacomy, M.*** *(2009) 'Gephi: An open source software for exploring and manipulating networks', in Third International ICWSM Conference, pp. 361–362. Available at: http://www.aaai.org/ocs/index.php/ICWSM/09/paper/viewFile/154/1009/ (Accessed: 13 March 2017).*

2 ***Jacomy, M.****, Venturini, T., Heymann, S. and Bastian, M. (2014) 'ForceAtlas2, a continuous graph layout algorithm for handy network visualization designed for the Gephi software', PLOS ONE, 9(6), pp. 1–18. doi:10.1371/journal.pone.0098679.*

Visual Network Exploration for Data Journalists (2018)

Book chapter.[3]

What Do We See When We Look at Networks? (Under review in Big Data & Society)

The document presented here is the first revision after peer-review, as sent to the journal *Big Data & Society*,[4] 2020-08-19.

EXPLORING THE MULTIPLE UNDERSTANDINGS OF NETWORKS

The third group of papers explores different understandings of networks, their visualization, and their analysis. In "Actor-Network vs. Network Analysis vs. Digital Networks,"* Tommaso Venturini, Anders Munk, and I unpack the confusion about the term *network* and its different meanings in the field of science and technology studies (STS). In "Unblackboxing Gephi,"* Emilija Jokubauskaitė and I account for network practices with Gephi, and I argue that they bear some responsibility for enacting VNA as an unsituated practice. In "Epistemic Clashes in Network Science,"* I map a controversy in the field of network science. I show that the network is a disputed object, and that, even within the natural sciences, it does not necessarily come with methodological commitments such as the scale-free model.

Actor-Network vs. Network Analysis vs. Digital Networks (2019)

Book chapter.[5] The book received the Olga Amsterdamska Award from the European Association for the Study of Science and Technology.

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3 *Venturini, T.,* ***Jacomy, M.****, Bounegru, L. and Gray, J. (2018) 'Visual network exploration for data journalists', in Franklin, B. and Eldridge, S. A. (ed.), The Routledge handbook to developments in digital journalism studies. Abingdon: Routledge.*

4 *Venturini, T.,* ***Jacomy, M.*** *and Jensen, P. (under review in Big Data & Society) 'What do we see when we look at networks: Visual network analysis, relational ambiguity and force-directed layouts'.*

5 *Venturini, T., Munk, A.K. and* ***Jacomy, M.*** *(2019) 'Actor-network vs network analysis vs digital networks: Are we talking about the same networks?', in Vertesi, J. and Ribes, D. (eds.), Digital STS: A handbook and fieldguide. Princeton, NJ: Princeton University Press, pp. 510–524. Available at: https://digitalsts.net/wp-content/uploads/2019/11/32_digitalSTS_Actor-Network.pdf (Accessed: 02 September 2020).*

Unblackboxing Gephi (under review in Science as Culture)

This article has been submitted to *Science as Culture*.[6]

Epistemic Clashes in Network Science (2020)

Published in *Big Data & Society*.[7]

INTERVENTIONS IN THE PRACTICE OF VNA

The fourth and final group of papers (one of which is a draft) intervenes in the practice of VNA itself. In "Translating Networks,"* Martin Grandjean and I propose a table of correspondence between visual features and statistical metrics, and we discuss the remaining gaps in such translations. "Connected-Closeness"* and "Simmelian Distance"* are two algorithmic and design interventions aimed at providing context to the interpretation of network maps. The first proposes a meaning for the visual distances between the nodes of a network map by articulating them with the presence of links, and the second, an early draft, aims to provide a deterministic model of visual distances as a way to compare and discuss different algorithms. These two documents feature mathematical formalism, while my arguments are mainly developed in Chapter 5 of this dissertation, "Interventions."

Translating Networks (2019)

This is a short paper published in the *Proceedings of the Digital Humanities Conference* in 2019.[8] The appendix proposes a table of correspondence between visual patterns and statistical metrics.

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6 ***Jacomy, M.*** *and Jokubauskaitė, E. (under review in Science as Culture) 'Unblackboxing Gephi: How user cultures shape their scientific instruments'.*

7 ***Jacomy, M.*** *(2020) 'Epistemic clashes in network science: Mapping the tensions between idiographic and nomothetic subcultures', Big Data & Society, 7(2). doi:10.1177/2053951720949577.*

8 *Grandjean, M. and* ***Jacomy, M.*** *(2019) 'Translating networks: Assessing correspondence between network visualisation and analytics', in Proceedings of the Digital Humanities Conference. Available at: https://halshs.archives-ouvertes.fr/halshs-02179024 (Accessed: 12 July 2019).*

Connected-Closeness (unpublished manuscript)

This is a draft paper[9] intended for submission to the *Journal of Graph Algorithms and Applications* or a similar journal.

Simmelian Distance (unpublished manuscript, early draft)

This document reveals the mathematics behind Simmelian distance. It is an early draft[10] on the argument level, albeit featuring mathematical formalism. The LaTeX format is more convenient to typeset equations.

A PRELIMINARY EXAMPLE OF VNA

I offer here an example of VNA. It was made specifically for this dissertation, and I ensured that it would be simple enough to bring home the point without becoming superficial. For brevity, I do not account for my practice. I only offer the resulting image and its explanation. The analysis is not very deep, but it showcases the type of argument that visual analysis offers. I was rigorous, and I combined statistical analysis with visual analysis. Unfortunately, proposing a technically precise example conflicts with the need for clarity. Nonetheless, I made the choice to use technical terms, assuming that even if some readers did not fully understand them, they would still be able to follow my general argument, which is paramount.

I analyze Figure 5, which represents *Wikipedia* articles around the concept of Europe. Take a minute or so to look at it, possibly taking note of your own interpretation. Next, I offer my own reading.

PRESENTATION OF THE DATA AND THEIR VISUALIZATION

This image represents a data set consisting of *Wikipedia* articles and a special kind of link between them. At the end of most *Wikipedia* articles, there is a “see also” section where one can find links to related articles, which can be found in the data set. Using the dedicated tool SeeAlsology,[11] I gathered every article with three links or less from a single starting point, the article on Europe. I then iteratively removed articles with 0 or 1 neighbor, considering them as insufficiently

9 ***Jacomy, M.*** *(unpublished manuscript) ‘Connected-closeness: A visual quantification of distances in network layouts’.*

10 ***Jacomy, M.*** *(unpublished manuscript) ‘The Simmelian distance: A latent space to model force-driven network layouts’.*

11 *https://densitydesign.github.io/strumentalia-seealsology/*

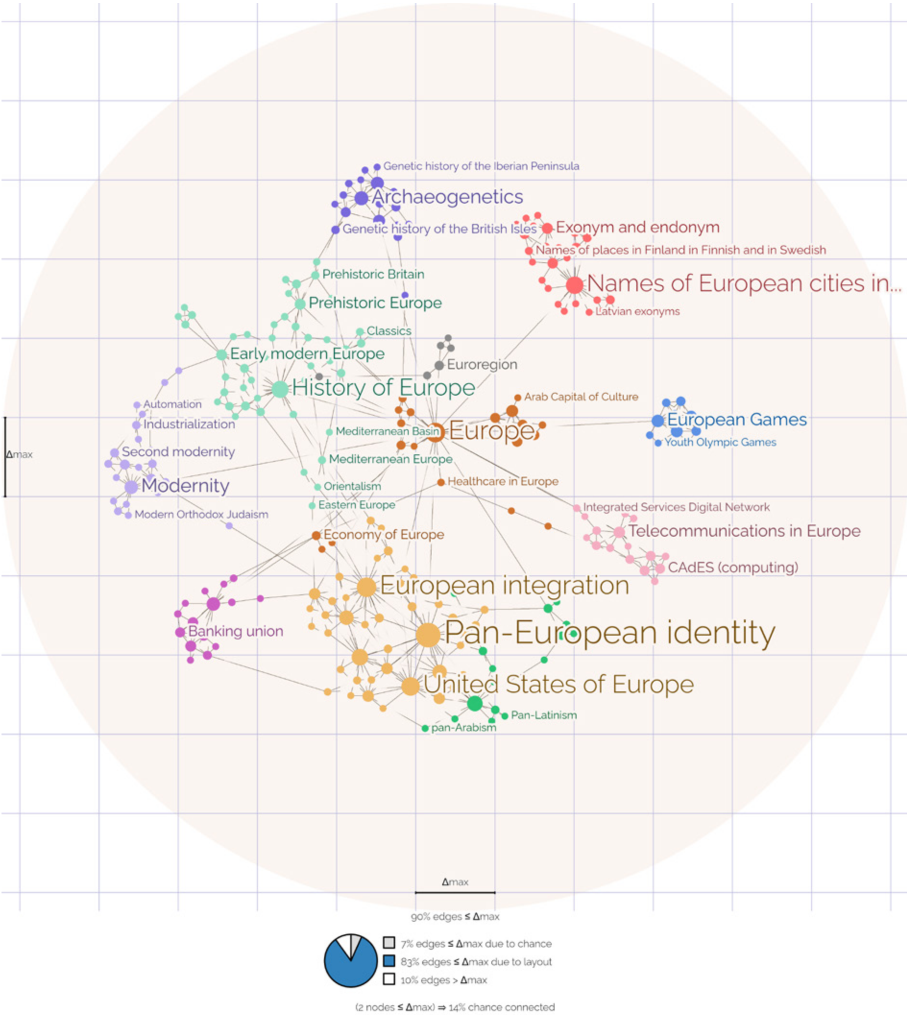

Figure 5. Wikipedia articles on Europe. Each dot represents an article. Each line represents a "see also" link between two articles. The colors have been computed by a community detection algorithm. The layout used is Force Atlas 2 LinLog. The effect of the layout is to bring 83% of the connected dots closer than Δ_{max}. The distance Δ_{max} is represented as a grid.

interesting because they did not contribute to the paths between the other articles of the corpus. The set ultimately contained 249 articles and 631 "see also" links.

Each dot (and, when present, its label) represents a single article from this data set, and bigger dots represent articles with more links. Some labels have been omitted to prevent overlaps, giving priority to the articles with the most links (presumably the most interesting in the structure). The dotted colors were obtained from a community detection algorithm (Blondel et al., 2008) and are a visual help to facilitate writing about the network. I do not use it for the analysis.

Each line represents a "see also" link. These links are oriented, but their direction is not represented here. The lines fade away when they come close to the dots they are not connected to, which is a visual help in determining which articles are linked.

The position of the dots is determined by the structure, the links. A force-directed placement algorithm ("Force Atlas 2"*) tries to bring connected articles closer. The result is isotropic: space is equivalent in any direction, so there are no axes (despite what the grid may suggest), and the placement could be rotated or flipped freely. Contrary to a scatter plot, the positions are not intended to be interpreted in terms of (x,y) coordinates but in terms of *relative distances*. We can clarify the effect of the layout with a distance noted Δ_{max}, represented visually as a grid. The layout succeeded in bringing 90% of the connected dots closer than Δ_{max}. In other words, most lines should be short, but this is not always possible, and some (10% in this example) remain long. These represent articles that are close in the structure (they are linked) but had to be placed at a distance in the image.

ANALYSIS

The *Wikipedia* articles in the data set are not uniformly linked. A few receive many links, while most only have a few. The most linked articles are "Pan-European Identity" (37 links), "Europe," and "European Integration" (27 links each). Conversely, 94 articles only have two links (the minimum allowed by my methodology). This distribution is expected and roughly follows a power law.

The most prominent feature of the image is the presence of clusters, emphasized by colors. As the placement manifests the structure, most of the links fall inside these node gatherings. I now describe these groups and interpret their features, but for purposes of brevity, I omit how I obtained the numbers.

The biggest group, with 50 articles (20% of the total), is in pale green, on the top-left around the article “History of Europe.” It is indeed about history and pre-history, mostly about Europe but includes other topics. Its most internally cited articles are “Prehistoric Britain,” “History of Europe,” and “Age of Discovery.” It is also the second densest group (with a normalized internal density of 0.032).

The second biggest group, with 43 nodes (17% of the total), is in yellow, at the bottom around “Pan-European Identity.” It mostly revolves around the political project of Europe. Its most internally cited articles are “Pan-European Identity,” “United States of Europe,” and “European Integration.” Some of the less cited articles are not about Europe, for instance, “United States of Africa.” It is the densest group (with a normalized internal density of 0.048).

In fact, all 11 groups are quite dense, with nine of them having a normalized internal density of 0.013 or more. In comparison, the highest normalized density from one group to another is 0.002 (which is from the yellow group to its neighbor, the green group, just on its right). In other words, the groups are quite well formed, despite the bridges between them. The visual intuition is confirmed by measuring the density.

Each cluster seems to have a theme. Clockwise, we have:

- In red on the top-right are articles on **naming** (“Names of European cities in different languages,” “Toponomy” and “Exonym and Endonym”)
- In blue on the right are articles on **international games** (“European Games,” “Commonwealth Games” and “World Games”)
- In pink on the right are articles on **telecommunications** (“Telecommunications in Europe” and “European Telecommunications Standards Institute”)
- In yellow and green on the bottom-right are articles on **Europe as a political entity**. I do not see a topical difference between the two clusters found by the community detection algorithm (yellow and green). Example of articles: “European Integration,” “Pan-European Identity,” “Pan-European Nationalism,” and “Fourth Reich”
- In fuchsia on the bottom-left are articles on **economy and bank** (“Economy of the European Union,” “European Central Bank” and “Capital Markets

Union")

- In mauve on the left are articles on **modernity**, unrelated to Europe ("Modernity," "Postmodernity" and "Industrial Revolution")
- In green on the top-left are articles on the **history of Europe** ("History of Europe," "Early Modern Europe" and "Prehistoric Europe")
- Finally, in purple at the top are articles on **genetic history** ("Genetic History of Europe," "Archaeogenetics" and "Genetic History of Indigenous Peoples of the Americas").

The central cluster, in orange-brown, does not have a clear topic, and its central article "Europe" is not strongly linked. It cites 26 other articles in its "see also" section, but it features in the "see also" section of a single article of this corpus ("Integrated Services Digital Network"). Europe is featured in the center because it is evenly distant from other clusters, as the methodology uses it as a starting point, but it does not appear as central as other highly cited articles. The most cited overall is "Pan-European Identity," present in the "see also" section of 15 articles of the corpus.

Takeaways

In *Wikipedia*, the different facets of Europe are split into different groups of articles: politics, history, economy, etc. Each group contains a number of articles that tend to cite each other in their "see also" section and tend *not* to cite outside of their group. The most important topics, both in terms of number of articles and link density, are *politics* and *history*. Except for one group (*modernity*), each group is focused on Europe. However, the article on Europe itself is poorly cited; the structure suggests that Europe is too generic to be featured in most "see also" sections.

VISUALIZING IS ALSO EXPLORING

Before we move on, I need to make it clear that the example above fails to represent an important part of the visual practices involving networks. Indeed, before the visualization is nice and clean enough to be shared, exploration may have taken place. By nature, exploration is a much messier process. During this phase, one iterates different ways of visualizing the network (data filterings, layout settings, semiotic tunings). Different hypotheses are considered and are gradually reduced by trial and error. As we will see, Tukey (1977) formalized this as exploratory data analysis (EDA). Even though the goal is different, the visualizations are interpreted in the same way, by looking at the distribution of nodes and edges. I will return to this question in the next chapter.

A final remark: you will find two other visual network analyses in the attached papers: one in “Visual Network Exploration for Data Journalists”* on the French media landscape, based on web data, and another one in “What Do We See When We Look at Networks?”* on Jazz and based on *Wikipedia* data.

PROBLEMATIZATION

In this section, I explain my endeavor and present the problematic of network maps by introducing the theses of this dissertation: (1) VNA consists of practices that are only partially determined by the graph-drawing and data visualization literature; (2) some visualizations, including network maps, prompt a visual inquiry into the meaning of the emergent patterns, which contributes to their apparent self-evidence; (3) for historical reasons, the graph-drawing literature mainly promotes an interpretation regime adapted to small networks (*diagrammatic*), with practices partially shifting, during the 2000s, to large networks (*topological* interpretation regime); (4) some issues with reading network maps can be attributed to the misalignment between our visual cognition and the computational standpoint, notably about the notion of the group; (5) the existing justifications of algorithm designers do not provide a compelling explanation of what we see in networks; and (6) the literature on *community detection* focuses on clear-cut clusters, while force-driven placement algorithms make visible other non-clear-cut community structures. To sum up, the question of network maps boils down to the question of *how to characterize the structures made visible by force-driven layouts*.

Let me start with a remark about terminology. I call the dot-line visualizations similar to the one in Figure 5 “network maps.” This name is quite common, but it requires a warning: it does not mean, and I do not mean, that these representations are, strictly speaking, maps. The geographical map is the closest familiar object to a network map, hence the name; but there are also differences. I present two remarks. First, in the paper “Force Atlas 2,”* published in 2014, I use the term “map” instead of “network map.” I now consider this terminology a mistake because it creates a misunderstanding. Second, you will find an elaboration on the similarities and differences with geographical maps in “Visual Network Exploration for Data Journalists”* (see section on Understanding Force-directed Layouts, 266–268). In short, the term “map” has been used since the first drawings of networks, framed as a "new geography" (Moreno, 1933), and drew on the familiarity of transportation maps. Networks were also called maps in STS, as Bruno Latour narrates: "I don't think it came from a great theoretical insight at the time. We had co-word analysis, which was called maps … [and] we thought that mapping as an orientation could be combined with code and algorithms. It was a mix or maybe a mess of ideas" (quoted from Venturini and Munk, 2021). It has always been established that network maps require specific reading rules. I retrace the history of graph drawing and its aesthetic criteria in Chapter 3.

So much has been written on graph drawing, community detection, and data visualization that it may seem that the question of network maps has somehow been resolved. For sure, they have their own issues, such as the "hairball" problem (Edge et al., 2018), where dense networks are rendered as hopelessly cluttered and packed balls of nodes. In the academic literature, hairballs are often mentioned to highlight the inherent limitations of dot-line drawings, for instance, to valorize sparsification methods (Dianati, 2016; Nocaj et al., 2015). Others contend that dot-line diagrams "encounter scalability problems" with large graphs (Von Landesberger et al., 2011: 1724) or measure that "matrices outperform them about large and dense graphs" (Ghoniem et al., 2005: 129). For small networks that are not too dense, however, the belief is that network maps are fine. It seems that the academic literature has settled the strengths and weaknesses of network maps. To some extent, it has. The pioneer age of networks is behind us, and network visualization has been commoditized. Is there still something worth discussing? From my point of view, *everything*.

Network visualization has always been a practice that precedes a theory, which is neither special nor surprising. However, in the gap between theory and practice, a misunderstanding thrived. Small networks remained the standard for evaluating graph drawing long after practices had shifted to large networks. Reading a small diagram is about following the paths, while reading a large network map is about understanding the link structure. Recent literature has acknowledged the importance of this mode of interpretation (Kypridemou et al., 2020; Soni et al., 2018), but the practice is much older, showcased in Adamic and Glance's (2005; see Figure 2) seminal work. Meanwhile, VNA was popularized without much critical perspective. Community detection and centrality metrics became routine in network analysis and, with them, the need for visualizing clusters and node attributes. Force-driven algorithms settled as the go-to solution to visually manifest the community structure, a methodological option backed by Noack's (2009) decisive claim that *modularity clustering is a force-directed layout* (modularity is a popular community-detection strategy). However, the notions of the group and community structure remain highly problematic: their multiple sociological meanings (Freeman, 1992) have important differences with the computational perspective (Fortunato 2010; Labatut and Orman, 2017) and network visualization (Bennett et al., 2007). In particular, the computer science literature often operationalizes community structures as sets of clear-cut clusters (Fortunato 2010), although not always (Good et al., 2010; Peixoto, 2020; Yang and Leskovec, 2014). In my observations, most scholars who practice VNA operate under the assumption that layouts make clusters visible; but what are "clusters" in this context? It seems to me that the community-revealing virtues of force-driven layouts consist of a tacit agreement based on experience and shared within certain scientific cultures. Unfortunately, this led the evaluation of VNA into an experimenter's regress (Collins, 1981), a loop of dependence between theory and evidence: in order to judge whether algorithms show clusters, we must rely on theory-based expectations of community structure, but to judge the value of competing theories, we rely on what algorithms produce (e.g., community detection). Ultimately, we know that force-driven layouts and modularity clustering show approximately the same structures, but we are unsure of what they are. Therefore, it is not very surprising that scholars struggle to make visible the VNA layers of mediation. Thus, the question of network maps is as follows: **what characterizes the structures made visible by force-driven layouts?** Of course, to escape the experimenter's regress, this characterization must not rely on force-driven algorithms or their equivalent (modularity clustering).

The most visible sign that the question of network maps is still open is the existence of a long-lasting criticism. Drucker (2014: 125) calls this new apparatus adopted by scholars in the humanities an "intellectual Trojan horse" whose assumptions "are cloaked in a rhetoric taken wholesale from the techniques of the empirical sciences." In fact, network maps perform more than just conveying scientific knowledge, as illustrated by their iconographic use outside academia (Figure 6). Within science, too, network maps are easily instrumentalized in the politics of methods (Ruppert and Scheel, 2019), which is a question of *situatedness*. I owe this reference to Haraway (1988) to Noortje Marres (2012), Ruppert and Scheel (2019), and Wieringa et al. (2019). Their perspectives criticize that "visualizations bring realities performatively into being" (Ruppert and Scheel, 2019: 8), pointing, for instance, to "Gephi's (lack of) 'epistemological affordances'" (Wieringa et al., 2019: 283). The question they ask is the same: where is the ground that allows us to critically re-examine the knowledge offered by network maps? This question has levels. It also begs the question of whether there is such a ground and, if so, how to find it. Moreover, why is it inaccessible? For Wieringa et al. (2019: 281) "Gephi is a perfect showcase to pose the question of the reflexivity of (algorithmic) knowledge instruments, or what becomes visible in comparison to the parts of the epistemic process that stay invisible." For them, Gephi lacks the features necessary to provide researchers "with the opportunity to scrutinize [the politics of the developer's community] in order to make sense of the interpretative acts performed" (Wieringa et al., 2019: 287). As a consequence, the visualization that one can produce "offers an unrestricted vision from above, a vision that allows us, in the tradition of the 'god trick' described by Donna Haraway (1988: 581), to see 'everything from nowhere'" (Ruppert and Scheel, 2019: 11). The invisibility of methodological commitments, they say, partially determines how a network map is received by its readers, for instance, as self-evident knowledge. "Crucially, the map's capacity to build allies derives precisely from making absent all the work that goes into the map's crafting" (Ruppert and Scheel, 2019: 11). In response to this issue, some researchers advocate promoting "awareness of the layers of mediation network analysis implies" (Rieder and Röhle, 2017: 118), for instance, by "facilitating systematic

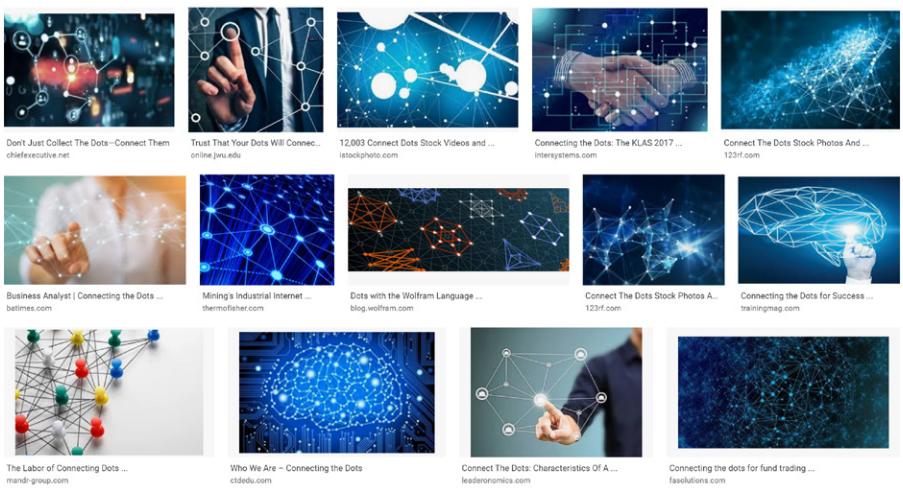

Figure 6. Examples of network imagery outside of academia. Google Image results for "connecting the dots" (Accessed: 01 September 2020). Google and the Google logo are registered trademarks of Google LLC (used with permission).

documentation of the visualization and analysis process [and by] mapping the interaction between the software tool and the researcher" (Wieringa et al., 2019: 293).

I titled this dissertation *Situating Visual Network Analysis* following Haraway (1988), of course, and because the mundane understanding of "situating" is a fine entry point. If you do not know Haraway's work, "situating VNA" probably sounds like *describing the context of VNA*. This is an acceptable simplification, as the multiplicity of the situations will appear naturally as my inquiry progresses. Indeed, there is not just one situation but many, and accounting for some of them will lead us to meet different publics, such as Gephi beginners, data visualization scholars, and algorithm designers. Their perspectives, of course, differ. There is one central question about the structures manifested by force-driven layouts, but it arises in multiple situations (Munk et al., 2019), and its answer is many-sided. As a tool maker, I seek to contribute to situating VNA, notably by making the underpinnings of layout algorithms more accessible; but there is no single path to addressing the network map issue. Furthermore, I am well aware that such an intervention will probably produce unexpected results, but this is not a reason to remain inactive. At the end of this dissertation, I propose two different "tinkerings," to reuse Mol's (2006: 410) metaphor. Although she writes about care, her words elegantly describe my endeavor: it "is not a matter of separating out elements, fixing them, and putting them to use in a linear manner. It is a matter of tinkering, of doctoring, if I dare to reclaim that word from the negative connotations it has acquired and give a positive appreciation to the creative calibrating of elements that make up a situation, until they somehow fit—and work."

I do care about VNA, and I do care about Gephi users, but our scientific apparatus is not a well-defined machinery known and mastered by a caste of tool engineers (or designers or computer scientists) to which I would belong. Our scientific apparatus has been largely co-designed by its practitioners (scholars, teachers, students, etc.) and shaped by the cultures within which it derives meanings. My intervention cannot consist of "fixing" a broken part of our knowledge apparatus, but it may be "doctoring" our relation to Gephi, force-directed layouts, and more generally the visualization of large networks. I can offer tinkerings "until they somehow fit—and work" (Mol, 2004: 410).

INTERPRETING NETWORKS VISUALLY IS A CHALLENGE[12]

The main challenge for network map readers is to figure out what they can trust and why. "Can a colorful visualization in *Gephi* alone provide sufficient evidence that Twitter conversations around a hashtag are polarized?" ask Theocharis and Jungherr (2020: 2). VNA is a popular but criticized practice where scholars rarely justify their visual interpretations (Bruns, 2012; Rieder and Röhle, 2017). In "Unblackboxing Gephi,"* Jokubauskaitė and I account for the difficulties of scholars in providing a meaningful reading of the network maps they produce. We observe shortcut practices where they sacrifice methodological accountability in time-constrained situations. More generally, we observe their struggle in interpreting the mediations involved in network visualization. In fact, there is no general methodology for interpreting networks visually in a research setting (Decuypere, 2020). This situation is not uncommon. Other scientific methods have been normalized because they are useful in practice, despite known flaws. For example, *p-values* have long been heavily criticized (Ioannidis, 2005) and are known to be widely misused (Sterne and Smith, 2001), yet they remain popular (Cristea and Ioannidis, 2018).

The problem is not caused by simple readability issues (e.g., occlusion or poor contrast). After all, the field of information design has extensively theorized how we interpret data visualizations. Unfortunately, the problem runs deeper than readability and comes from our inability to predict or explain the outcome of the algorithmic process of placing nodes, in a Euclidean space (e.g., the screen), according to the topology of their connections. This process is generally called *graph embedding*, and when it comes to VNA, we refer to it as a force-driven *placement algorithm* (there is a nuance, but I overlook it for the moment) or, more simply, a *layout*. We can explain how these algorithms work, but we cannot explain the placement they produce. We have no formal model of the resulting node distances. Our ability to produce these results does not suffice to understand them, the same way that the laws of thermodynamics do not suffice to explain why sand makes dunes. The co-authors and I develop this question in "What Do We See When We Look at Networks"* and "Translating Networks."*

One may find it surprising that scientists make significant use of a technique that lacks formal justification. There is a specific reason for this: network visualization

12 This section draws on an essay I self-published on my research blog titled "The problem with network maps."
https://reticular.hypotheses.org/1724

is not used primarily to produce evidence but to produce hypotheses. This point has been made by Tukey (1977) in his theorization of EDA. It is not a problem of science that the visual interpretation of networks is uncertain; certainty is provided by other means. The role of the visual is to generate hypotheses and share insights. In my earlier example (Figure 5), I used statistical metrics to ground my points. The visual was used upstream, to help me find the relevant points to make, and downstream, to share my insights with the reader. For an analysis to be performed, one needs hypotheses, precisely what network maps generally provide.

An uncertain reading is not necessarily an issue in practice, but there are other problems: (1) the lack of reproducibility and Popperian falsifiability fail to meet some science standards; (2) the knowledge being implicit makes it more difficult to teach and disseminate; (3) people might misconstrue the apparent lack of methodological foundations as a form of self-evidence, conflating the data and their representation; and (4) it makes it difficult to discuss and criticize the process of visualizing networks and improving it.

Indeed, even though VNA is not used to provide evidence, it shapes scientific practices and their outcomes. By influencing the hypotheses considered by the researcher, it partially determines the findings.

AN EXAMPLE OF BIAS: DIRECTED EDGES

I offer here an example of a bias that, while easily understood, is also easily overlooked. In a network map, our reading is mostly concerned with the distance between the nodes. This is how we can figure out clusters, structural holes, etc. Furthermore, distance is mutual, symmetrical. If A is close to B, then B is close to A. Unfortunately, in most directed networks, the all-important hierarchical effects come from the asymmetry of edges. You retweeting Pope Francis is not the same as Pope Francis retweeting you. The former is far less remarkable than the latter. When you look at a network map, because you look at the distances, by nature of the inscription support, you miss the asymmetries of the links. Of course, one can get some indirect clues, such as by sizing the nodes by the number of incoming links. While this helps, it is just mitigation. The real protection against that bias is to acknowledge it and to represent asymmetries with another visualization, for instance, a matrix.

This is the strategy that the co-authors and I use in "Visual Network Exploration for Data Journalists"*. Venturini, Bounegru, Gray, and I present a network of websites connected by hyperlinks. Although a community structure can be detected visually and statistically, the most important feature of the network is the asymmetry of the links between the pre-established categories. For this reason, we complement the network maps with diagrams and matrices displaying the extreme asymmetries of the digital public space (Figure 7).

In Chapter 4, I will document another bias of network maps in relation to clusters, which is not entirely due to the algorithm but also to our visual system. More generally, all visualizations have biases. Biases are not signs that a technique is defective; they are inevitable distortions that you must take into account when you interpret an image. Furthermore, accounting for the limits of the mediation is an integral part of situating a visualization.

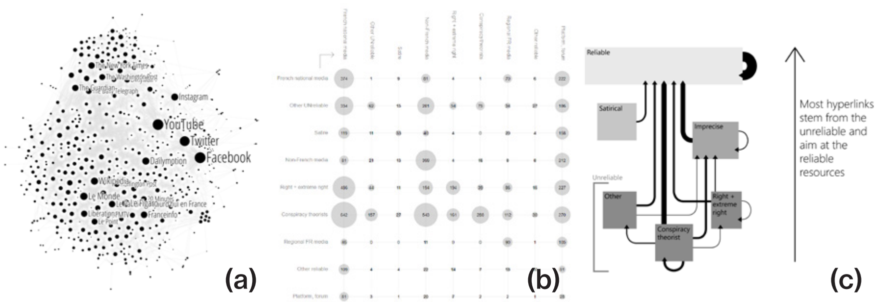

Figure 7. Figures representing the same network from "Visual Network Exploration for Data Journalists": (a) a dot-line diagram where the asymmetric links are not visible; (b) a matrix view of the groups, where asymmetries are visible, suggesting hierarchical relations; and (c) a diagram showing the strong hierarchical relations between the groups.*

SIMILAR BIASES ARE ALSO FOUND IN ALTERNATIVES TO NETWORK MAPS

A word on matrices versus dot-line diagrams (network maps): on the surface, these two strategies are complementary. Both have pros and cons, and there is a debate on which is better (for an overview, see Munzner, 2014: 201). However, at the core, they suffer from the same problem: they depend on a node placement algorithm. This might not be obvious for matrices, so let me explain. The patterns you see in a matrix strongly depend on the order of the rows and columns, which represent the nodes (Figure 8). The clusters or blocks appear in the matrix if similar nodes are next to each other, so it depends on an algorithm sorting the nodes. It is a one-dimensional (and discrete) placement instead of a

Figure 8. The Wikipedia articles on Europe visualized as an adjacency matrix. The rows and columns represent the articles; the blacked cells represent a "see also" link. On the left, the nodes have been ordered by decreasing the number of inbound links. On the right, the nodes have been ordered using the same community detection algorithm used to colorize the nodes in Figure 5. The presence of blocks on the diagonal indicates clusters, but it depends on the ordering of the nodes.

two-dimensional (and continuous) one, but the algorithmic strategy is exactly the same (for an in-depth assessment of this issue, see Behrisch et al., 2016).

According to Ghoniem et al. (2005), matrices are more efficient visualizations for dense networks, but they rely on the same disputed algorithmic strategy. Other strategies exist, but they all come with their own problems (for an overview, see Gibson et al., 2012).

THE ALGORITHMS WE USE ARE, IN PART, ARBITRARY

Finding an optimal node placement is hopelessly difficult (and even defining what "optimal" means is complicated, but I will return to this question later). It is said to be "NP-complete" (following Harel and Koren, 2000), which is a mathematical notion that characterizes problems as impossible to solve in polynomial time. As a consequence, in practice, we rely on approximations, and the most common strategy, force-driven placement, is non-deterministic. In "Force Atlas 2,"* my co-authors and I present the anatomy of such an algorithm. If you run it twice, you get two different results (but not necessarily *very* different). The fact that force-driven node placement algorithms are non-deterministic leads some critics to conclude that their interpretation is not reproducible. The argument sounds reasonable, but the situation is more complicated.

Determinism should not be the gold standard of visualization procedures. Indeed, it is possible to "seed" randomness so that it becomes deterministic, and it is possible to randomize a procedure to make it non-deterministic. In other words, we can easily add or remove determinism, but this operation is only superficial. It does not change the deeper nature of the algorithm. Determinism, here, stands for something else: independence of context. If the solution to the problem can change while its terms remain the same, then this solution depends on something exterior to the problem itself, which is arbitrary. The real problem is not the lack of determinism but dependency on an arbitrary factor. Indeed, there is an arbitrary element in force-directed layout algorithms.

The arbitrariness lies in the node placement endeavor itself. We give coordinates to nodes, but we do not actually use them. We only use a derivative: distances. Coordinates are, in a way, just a by-product. Indeed, contrary to other visualizations such as scatter plots, the axes do not matter. The algorithm, in its calculations, only considers the distances between the nodes. This is why, contrary to a scatter plot, we can freely rotate or flip the visualization. Rotating and flipping preserve distances, thereby preserving the outcome of the algorithm. The positions have no meaning (aside from defining distances). From the perspective of interpretation, force-directed layouts transform a node–node relation (edges) into another (visual distances). The node–space relation (coordinates) is, in this regard, unnecessary (Figure 9). Obviously, we need coordinates to draw the picture, but they introduce noise in the sensemaking process. They should not be interpreted, yet they are present, potentially eliciting inappropriate readings. Thus, the process of building network maps involves unaccountable decisions taken by the algorithm so that we can draw the picture. I believe that this situation is the root of many problems specific to network maps. Once we acknowledge it, there are a number of interventions we can make (Chapters 3 and 5).

OVERVIEW OF THE ARGUMENT

In Chapter 2 ("What is Visual Network Analysis?"), I replace VNA in its context. I provide different academic angles around it and describe it as a practice. I also explore criticisms of it from the social sciences and humanities. In Chapter 3 ("The Art of Drawing Networks"), I retrace the history of graph drawing, its algorithms, and their evaluation. I then propose a short state-of-the-art of the discipline, focusing on a force-directed node placement for static networks. By analyzing this material, I argue that **the aesthetic criteria of graph drawing do not account for current network practices**. Indeed, the historical perspective shows

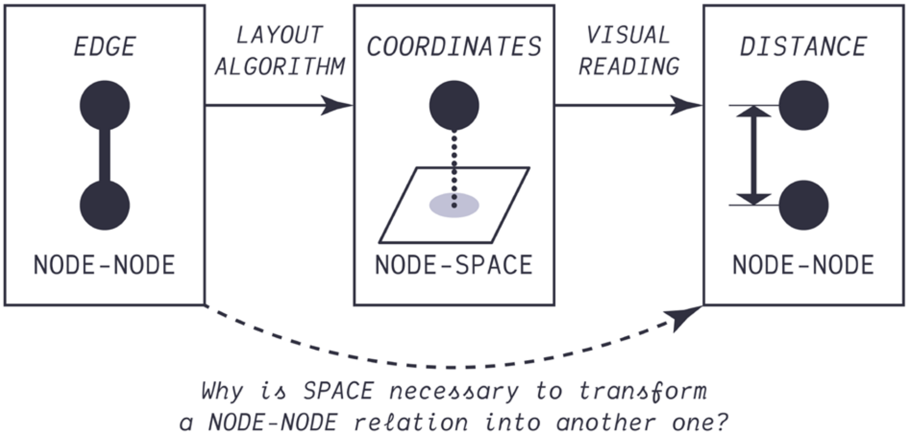

Figure 9. Important steps in rendering a network map. Node coordinates only determine the interpretation via the distances they produce between the nodes. Why is a node–space relation necessary if the output is, like the input, a node–node relation?

that aesthetic criteria are rooted in the tradition of diagram reading. However, in the 2000s, the need for network visualization shifted to large complex networks. I contend that new emergent practices accentuated a divide between algorithm designers and the evaluation literature. The practices moved to a different interpretation regime dedicated to the specific affordances of complex networks. The literature on graph drawing evaluation remained attached to the older aesthetic criteria, only recently acknowledging this shift. I refer to the older interpretation regime as *diagrammatic* and to the most recent as *topological*. My argument about the interpretation of distances in a force-directed layout is specific to the topological interpretation regime. Indeed, with a small network, it is possible to focus on readability and allow the visual retracing of the paths. Here, the nodes can be placed to support readability (prevent occlusion, edge crossings, etc.). On the contrary, large complex networks do not allow path retracing, and the main way for the image to mediate the topology is via the node placement. This, of course, entails a different evaluation approach.

In Chapter 4 ("What Do We See When We Look at Networks?"), I explore the hermeneutics of network maps by focusing on a state-of-the art algorithm, the LinLog, and its relations with two related questions: community structure (clustering algorithms) and our visual system (how we see groups). I show that the biases and flaws of network visualization are not only in the node-placement algorithm but also in its interactions with the network topology and our visual system. The notion of the *group* is not exactly the same in the topology and for the eye. By comparing the Gestalt model of groups to the implicit model of force-driven algorithms, I show that there is a mismatch in certain situations. In short, the algorithm ignores that our visual system requires gaps in order to see distinct groups. I explore the reasons given by algorithm designers to justify their efficiency, and I show that they do not really explain what we see in networks. I also show that simple explanatory models, such as "close nodes are connected," do not correspond to force-directed layouts. I argue that while these algorithms account for a community structure, this structure does not necessarily look like a set of clear-cut clusters. I call such structures *stretchings*. They are cluster-like because they are locally clustered (the friends of my friends tend to be my friends) but exist in other shapes than the densely packed ball that we usually imagine when we think of a cluster. I argue that the community detection literature has almost exclusively focused on community structure as a partition (where to cut clusters), to the detriment of other valid (although less convenient) community structures. I contend that force-directed layouts are specifically efficient at visualizing stretchings and that partition models are inappropriate benchmarks to evaluate them.

Finally, in Chapter 5, I propose two interventions to improve the practice of VNA. The first proposes a quantified interpretation of the distances in a layout. I show how to find the visual distance that captures the most edges in the layout, and my proposal is that it is drawn on the visualization so that we can build quantitative statements about the visual, for instance, "90% of edges are shorter than distance Δ_{max}." My second intervention proposes the computation of a node–node distance that mimics the behavior of a force-driven layout but does not require the arbitrariness of the node–space relation of coordinates. It is deterministic and can be used as a quality metric to compare layouts, networks, and algorithms.

2. WHAT IS VISUAL NETWORK ANALYSIS?

VNA is a practice that precedes a theory, but this does not mean that there are no theories involved. In fact, VNA draws on multiple fields, some of which are transdisciplinary. In this section, I provide complementary angles to understand the context of VNA. The first standpoint is the academic literature, which is itself fragmented. The second standpoint has to do with network practices. I propose a few observations about how researchers interact with network maps, either by making them or reading them. My third and final standpoint is the criticism of network visualization from the social sciences and humanities.

ACADEMIC PERSPECTIVES ON VNA

NETWORKS AND NETWORK VISUALIZATION

As Newman (2018: 1) elegantly puts it, "[a] network is, in its simplest form, a collection of points joined together in pairs by lines. … Many objects of interest in the physical, biological, and social sciences can be thought of as networks and … thinking of them in this way can often lead to new and useful insights." Networks help us shift our attention from substances to their relations, which has proven to be fruitful in many areas, such as sociology (Milgram, 1967; Moreno, 1934; White, 1963), biology (Jeong et al., 2001; Barabási et Oltvai, 2004), engineering (Yazdani and Jeffrey, 2011), and media studies (Bruns, 2012; Rieder, 2013; Rogers, 2013), to name a few.

Newman (2008) is a physicist known for his theoretical contributions to the study of networks, and I find it remarkable that, in his very mathematical book on the subject, *Networks*, he chose to introduce networks as something visual, favoring the dot-line diagram over the matrix representation often used in mathematics. This tells us something about how profoundly we tend to think of networks as dots and lines. However, in its purest form, a network is just a list of nodes and a list of edges. These nodes and edges often have attributes, and networks come in different varieties. Edges can be directed. Nodes and edges can be weighted. Parallel edges (edges between the same pairs of nodes) can be allowed or not, including self-loops (an edge from a node to itself). These are just some of the most usual varieties of networks, and while this bestiary does not matter much to this dissertation, I will mention network specificities when necessary (notably directed edges). It is also correct to refer to networks as *relational data*. This notion is useful in emphasizing the fact that a set of formal relations *de facto* constitutes a network. I stress that a network does not become one when it is visualized. Visualizing networks is not an obligation to study them, and processing relational data is a form of network analysis.

That being said, network visualization is undoubtedly relevant to the study of relational empirical phenomena such as technological infrastructures (the Internet, power grids), social interactions (affiliation networks), digital information (the World Wide Web, citation networks), and life (gene-protein interaction, neural networks, ecological networks). According to Newman (2008: 8), "Visualization can be an extraordinarily useful tool in the analysis of network data, allowing one to instantly see important structural features that would otherwise be difficult to pick out of the raw data. The human eye is enormously gifted at discerning patterns, and visualizations allow us to put this gift to work on our network problems." Dot-line diagrams, such as Figure 5, also called network maps, are not the only way to visualize networks, but they are the most common. The field of *graph drawing* is dedicated to this exercise (from a computer science perspective, i.e., algorithmic and rarely semiotic). However, networks have also been drawn by social scientists accounting for relational phenomena (e.g., Moreno, 1934). They have more recently become part of the "visual register" of STS (Jensen et al., 2014; see also Cambrosio et al., 2020) and, notably, for controversy mapping (Venturini and Munk, 2021).

Networks are not just one thing but many, depending on the epistemic culture appropriating them. This is not just a matter of natural sciences versus social sciences. In "Epistemic Clashes in Network Science,"* I discuss at length the different approaches to knowledge by experimentalists and theorists within the field of network sciences, considered closer to the natural sciences. On the STS side of social sciences, Munk, Venturini, and I discussed three different understanding of networks in STS in "Actor-Network vs. Network Analysis vs. Digital Networks."* The network is not a unified object, not even within a given field (see also Cambrosio et al., 2020). To set the scene, I now offer an overview of the main fields concerned with networks, including the differences between them.

NETWORK ANALYSIS AND OTHER FIELDS CONCERNED WITH NETWORKS[13]

The two main network-specific fields are social network analysis (SNA) and network science (NS). The scientific literature also mentions network analysis (NA), mostly referring to the practice of analyzing networks, and, by extension, methodological critiques of them (Figure 10). As VNA is a practice, NA is its natural context. It is, therefore, useful to clarify the nuances between the three notions.

Network analysis (NA) is a set of research practices that have progressively stabilized on specific methodological foundations. Although there is a relative consensus on its theoretical base, its practices are not unified. They include both what Erikson (2013) calls the *formalist* approach, based on a "structuralist interpretation" (networks are phenomena, e.g., in Georg Simmel's sociology), and the *relationalist* approach, which "rejects [the] essentialism" of the network (as an apparatus to know, e.g., in the natural sciences).

Although NA is primarily a practice, we can also see it as a field—a field about a practice that is much older than its formalization as a field. The overview proposed by Borgatti et al. (2009) places the point of origin of NA within the social sciences (with Moreno's (1934) sociograms), before it "radiated into a great number of fields, including physics and biology" during the nineties. For these authors, NA is not a field but a longstanding practice progressively formalized into SNA and, later, NS. However, other authors acknowledge it as

13 This section was republished on my research blog in a slightly reworked version as a post titled "In short: nuances between Network Science, Social Network Analysis, and Network Analysis."
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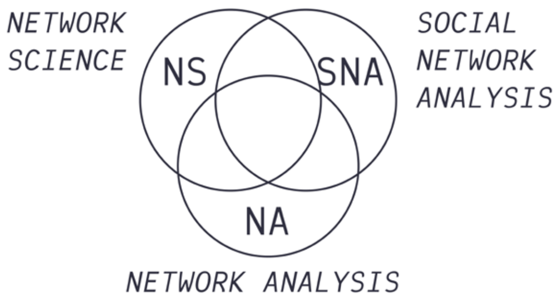


Figure 10. Network science (NS), social network analysis (SNA), and network analysis (NA) are three distinct domains. Although they overlap, each has its own specific knowledge and/or practices; none can be summarized as a combination of the others.

an independent field (Brandes and Erlebach, 2005; Chiesi, 2015) with its own methodological knowledge derived from graph theory and its own theoretical discussions (e.g., Barnes & Harary, 1983; Butts, 2009). Even so, NA is centered on practice. Brandes and Erlebach (2005: 1), for instance, have found that it is "adequate to treat network analysis as a field of its own." However, the authors add that "[f]rom a computer science point of view, it might well be subsumed under 'applied graph theory,' since structural and algorithmic aspects of abstract graphs are the prevalent methodological determinants in many applications, no matter which type of networks are being modeled." Similarly, for Chiesi (2015: 519), NA "can be regarded as a set of techniques with a shared methodological perspective." NA is part of other fields, including NS and SNA, as a *practice*. Nevertheless, as a *field*, NA is also concerned with the foundations of this practice. It has its own intellectual and cultural space.

Social network analysis (SNA) predates both NS and NA. Indeed, the network is a key idea to multiple schools of thought in the social sciences, from Moreno's (1934) sociograms to White's (1963) kinship models, Milgram's (1967) "six degrees of separation," Lévy-Strauss' (1973) structural anthropology, and Granovetter's (1973) "strength of weak ties." These long and rich considerations regarding the relational nature of the social coalesced into the field of SNA. In accordance with this thick heritage, the field sustains an in-depth discussion on the empirical nature of the networks it studies and pays close attention to the various methodological issues tied to the use of its instruments.

Network science (NS) emerged during the late 1990s as a "highly interdisciplinary research area" (Börner et al., 2007; see also Barabási, 2016; Hidalgo, 2016) around the object of the complex network. Graph theory is generally presented as its point of origin, more precisely, the random graph model (Erdős and Renyi, 1960). As scholars across various disciplines realized that their empirical networks were usefully described by the newly formalized concept of the complex network, theories of NS disseminated as an operational toolkit for analyzing networks. It is worth mentioning that the apparition of the web, and later social media, provided plenty of network data that called for the democratization of network analysis methods. "Epistemic Clashes in Network Science"* features an in-depth inquiry into the epistemic foundations of the field, including a presentation of its key concepts and an analysis of its main controversy.

NS, SNA, and NA are three distinct domains. The similarity in the names is unfortunate because it downplays differences that we cannot afford to overlook. I acknowledge the profound intricacies of the fields, and my attempt to make distinctions is not about enforcing a clear demarcation between them. Rather, I aim to clarify the fringe of knowledge and practices that are, in each field, incompatible with those of the other two (Figure 10). Indeed, despite their important overlap, key specificities subsist that notably explain that NA resists dissolving into NS and/or SNA.

Differences between NA and SNA. The differences boil down to the fact that, from the perspective of NA, a network is a set of inscriptions. NA is concerned with networks-as-data: it can be used with potentially any data set, as long as it is formatted as a network. Thus, it differs from SNA on two notable points: (1) NA is also interested in non-social networks (e.g., protein-gene interactions), and (2) it is not concerned with the gap between a social phenomenon and its reduction as a network. Since SNA is about networks-as-phenomena, it is deeply concerned about the part of reality that is left aside in datafied networks; for NA, the datafied network is a given. This is not to say that networks-as-data can dodge the ordeal of empirical validity; rather, this discussion takes place outside of NA, in the field where empirical data come from (e.g., molecular biology).

Differences between NA and NS. Contrary to NS, NA is aimed at describing networks. NS is a broad field with its own subcultures and practices, relatively united around the notion of the complex network; it comes with its own research questions, e.g., can we find universal laws capable of explaining the pervasiveness of complex networks? NA, by contrast, is quite agnostic in terms of research questions. It focuses on how to describe and account for a given network. Analyzing networks is part of what network scientists do, of course, but NA also extends beyond the domain defined by the research questions of NS. An idiographic account of a particular network does not typically meet the publication criteria of NS, contrary to media studies (e.g., Áragon et al., 2013), sociology (e.g., Adamic and Glance, 2005), or digital humanities (e.g., Grandjean, 2006). As an example, the journal *Network Science* (Brandes et al., 2013) publishes many types of papers, some of which are case-based, but none are *just* empirical accounts.

The overlap between NA, NS, and SNA. While the three fields aim to accomplish different things, they overlap in *how* they deal with networks. The algorithms and metrics used are largely the same, despite the presence of some specificities in each field. On a practical level, the three fields can easily meet. For instance, within the computational social sciences (Lazer et al., 2009), there are three intersecting dimensions: (1) the figure of the complex network and the practice of modeling, which is characteristic of NS; (2) the knowledge about the social of SNA; and (3) the empirical practice of NA. The techniques developed by NS were disseminated to SNA, but as Freeman (2008) narrates, some methods also travelled the other way around. This important overlap makes it tempting to simplify the situation by assuming that one of the fields subsumes or otherwise contains the other two (pick your favorite!). However, doing so blinds us to the epistemic trouble caused at the fringes of each field and by their peculiarities. As part of NA, VNA appears in both NS and SNA without being defined by either.

VNA AS A DATA SCIENCE PRACTICE

VNA is a specific way (using vision) of analyzing specific kinds of data (networks) (Figure 11). As a practice, NA draws from a larger pool of statistical techniques used in various fields. NA is naturally complemented by statistical analyses and does not exist as a separated approach. Classic statistics are an important part of NA, for instance, analyzing the distribution of a node attribute requires no network-specific technique, yet it is part of the network analysis process.

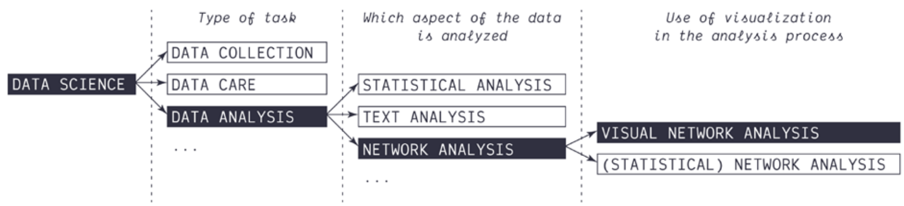


Figure 11. Conceptual analysis of VNA as a data science practice.

VNA is the practice of analyzing networks by visual means and nothing more. Jokubauskaitė and I account for such practices in "Unblackboxing Gephi,"* which narrates the difficulties encountered by Gephi users when they analyze networks visually. Contrary to NA, VNA is not a field, although it has been presented as a "qualitative research method" by Decuypere (2020) and Munk (2019), notably drawing on an earlier formalization attempt by Venturini et al. (2014). I have two reasons to characterize VNA differently from Decuypere. First, his VNA includes data collection and coding. Although these are legitimate steps in an analysis method, they are not specifically visual. Second, Decuypere does not take into account the problem specific to interpreting large networks. In short, while in small networks we look at the edges (because we can follow them visually), in large networks, we interpret the position of the nodes (because there are too many edges to follow). Venturini, Jensen, and I make this argument in "What Do We See When We Look at Networks?"* but I will elaborate further in the next chapter. From my perspective, the main challenge of VNA is to interpret the placement of the nodes, the layout. Decuypere places VNA in the continuity of the sociogram, the popular visualization practice in the field of SNA (Contandriopoulos et al., 2017; Moreno, 1934). This is true from a historical perspective, but sociograms are always small networks where the layout does not matter much. Analyzing small networks visually is neither specific nor problematic. I do not think that VNA qualifies as a method, considering the relative lack of interpretive approaches to large networks—although this dissertation might help.

VNA is often practiced in conjunction with statistical analysis (Grandjean and I propose a tentative articulation in "Translating Networks"*). As part of NA, it makes use of various data analysis techniques that are not network-specific. In "Visual Network Exploration for Data Journalists,"* we offer a detailed analysis where network visualizations are complemented with statistical metrics to compensate for a blind spot of network maps (link asymmetries), a point highlighted earlier (Figure 7).

The experimenter's regress of VNA

The experimenter's regress (Collins, 1981) happens when theory relies on evidence at the same time that evidence relies on theory, thereby making neither obtainable. Let me explain what this means by first remarking that VNA is, by nature, a composite practice. The visual analysis of large networks requires an algorithm (e.g., "Force Atlas 2"*), which makes the interpretive process unusually difficult to assess. Venturini, Jensen, and I discuss this issue in "What Do We See When We Look at Networks,"* and I will unfold it further in this dissertation. Visual analysis deals with a multilayered problem: interpreting an image that depends on an algorithm that depends on a graph structure. We use the algorithm to understand the structure, assuming (1) that data visualization tells us how to read the image, (2) that graph drawing tells us how the node placement is determined by the structure, and (3) that graph theory defines what the structure of the network is. However, the situation turns out to be a gridlock or, if you prefer, a Mexican standoff (Figure 12). Indeed, data visualization can tell us how to

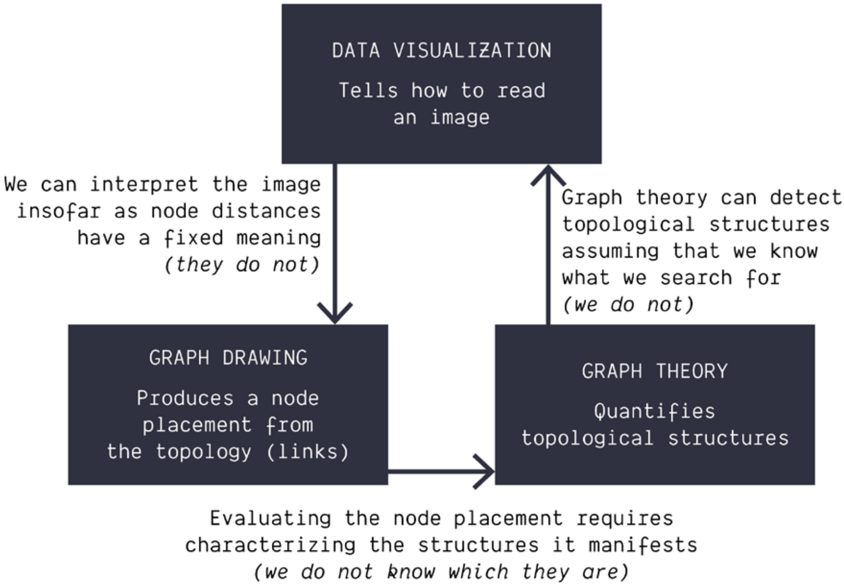


Figure 12. The Mexican standoff of VNA: each field's contribution depends on another field.

interpret the node placement (i.e., node distances), but it assumes that we know what this means—something we do not know because the field of graph drawing only offers procedures to produce the placement, not explanations. Evaluating the layout as a mediation requires knowing which topological structures are translated into the node placement. Graph theory offers various characterizations of topological structures, but it does not tell us which ones are relevant. The structure we should use as a benchmark to evaluate node placement algorithms should be that which is useful to us in the practice of VNA. This ties back to our starting point: the structure manifested by the layout should be whatever we are used to seeing.

This Mexican standoff illustrates an experimenter's regress (Collins, 1981) distributed over multiple disciplines. Here, theory and evidence depend on each other. Evaluating the ability of the layout to produce reliable evidence requires a theory of how it mediates topological structures, but building such a theory requires understanding what layout algorithms make visible in practice. This dependency loop prevents us from describing VNA as a theory; it is better characterized as a practice. I propose a more detailed description of the regress in Chapter 4 (Figure 59).

VNA AS A MEDIATED ENGAGEMENT WITH DATA

VNA, as a practice, relies on instruments. With Gephi and Force Atlas 2, I have contributed to this apparatus ("Gephi"*; "Force Atlas 2"*). As Jokubauskaitė and I argue in the discussion part of "Unblackboxing Gephi"* (p. 18), the instruments of VNA are mediations. In Figure 13, I propose a basic model of the layers of mediation involved. Computing the layout (node placement) is one of the most difficult mediations to assess, which I argue. However, all of these mediations matter insofar as forgetting about them enacts network maps as unsituated.

In "Unblackboxing Gephi,"* we argue, following Latour (1994), that instruments act, displace goals, and contribute to their redefinition. We contend that network maps constitute an "epistemic surplus" of Gephi, to reuse Rieder and Röhle's (2017) expression. Gephi redefines the goals of its users by making it easy to produce network maps. Moreover, the culture of its users symmetrically shifts the goals of the tool, emphasizing its ability to produce images. Thus, the VNA apparatus contributes to the circulation of unsituated knowledges. I develop this point at the end of this section.

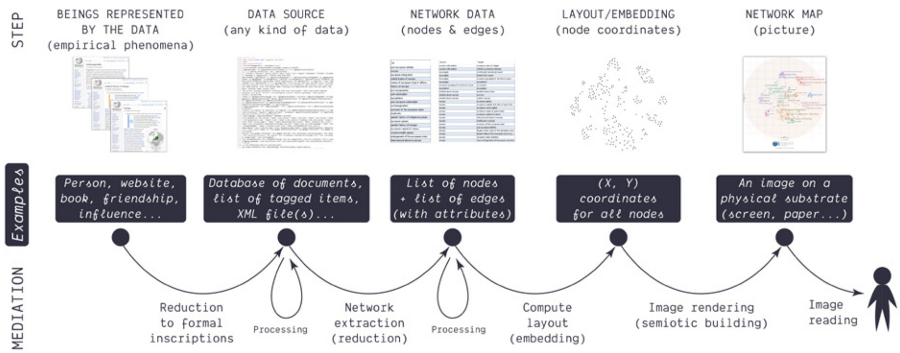


Figure 13. Layers of mediation involved in VNA.

VNA AS A (BIG DATA) VISUALIZATION METHOD

Following the practice, VNA mostly relies on network maps as a visual device, although it is sometimes complemented by the classic arsenal of statistical charts (bar charts, curves) and other network visualization techniques (matrices). If we exclude the question of node placement, network maps are pretty close to traditional geographical maps. Like local maps (e.g., a city, though not the whole globe), their projection space is isotropic, i.e., equivalent in every direction. Visualizing a network involves the same semiotic thinking about preventing cluttering, thus favoring clarity and prioritizing the right visual variables involved in crafting a map. For specificity in terms of data visualization, network maps have to involve the algorithmic process of node placement (which we can consider a form of spatial projection). Node placement is a major issue, though, as I have already argued. I will return to this point.

I find it useful to frame network maps as *big data* visualizations. Kitchin (2015) observes that many statisticians refer to the "3Vs" of big data: volume, velocity, and variety. I consider that the complexity of networks ultimately comes from their two heterogeneous parts, the nodes and edges. As such, I tend to see networks, and their complexity, as part of big data. For small networks, the point is debatable, but large networks clearly check another V: volume (Figure 14). This is no surprise if we mind that emergence and complexity are common ideas in big data and complex networks. However, more than networks as data, it is network maps *as visualizations* that I want to frame as big data. For big data visualizations, in general, the question arises as to how readers account for the many layers of mediation involved, including the necessary computations.

My motivation is to account for the politics of method involving network visualization. Indeed, as observed by Ruppert and Scheel (2019), visualization plays a central role in the power of conviction of big data. I contend that network maps have a similar power of conviction because they share essential features with the non-network visualizations of big data. I will take this argument further. For the moment, let me simply characterize big data visualization in a way that naturally includes the network maps of large networks.

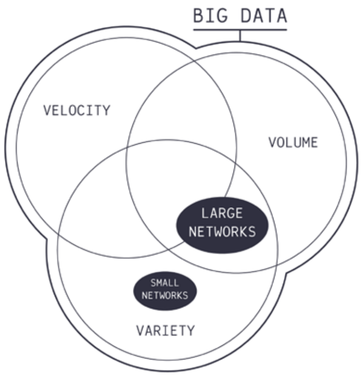


Figure 14. Networks in the context of big data.

Characterization of big data visualizations

By "big data visualization," I refer to a specific type of image commonly associated with big data, which shares the following characteristics:

- **A proliferation of signs.** The visualization features a high number of signs usually associated with data points. This includes dynamic visualizations distributed over time.
- **An internal order.** As the image or video pictures data, there are presupposed rules or constraints to these elements. They may be stated in a key or

caption or left implicit but visible in the image.

- **Emergent patterns.** Together, the signs display shapes not prescribed by the internal order. This emergent order may or may not be recognizable.

Non-network examples are featured in Figure 15. In a nutshell, the two important features are the proliferation of signs and the presence of emergent patterns.

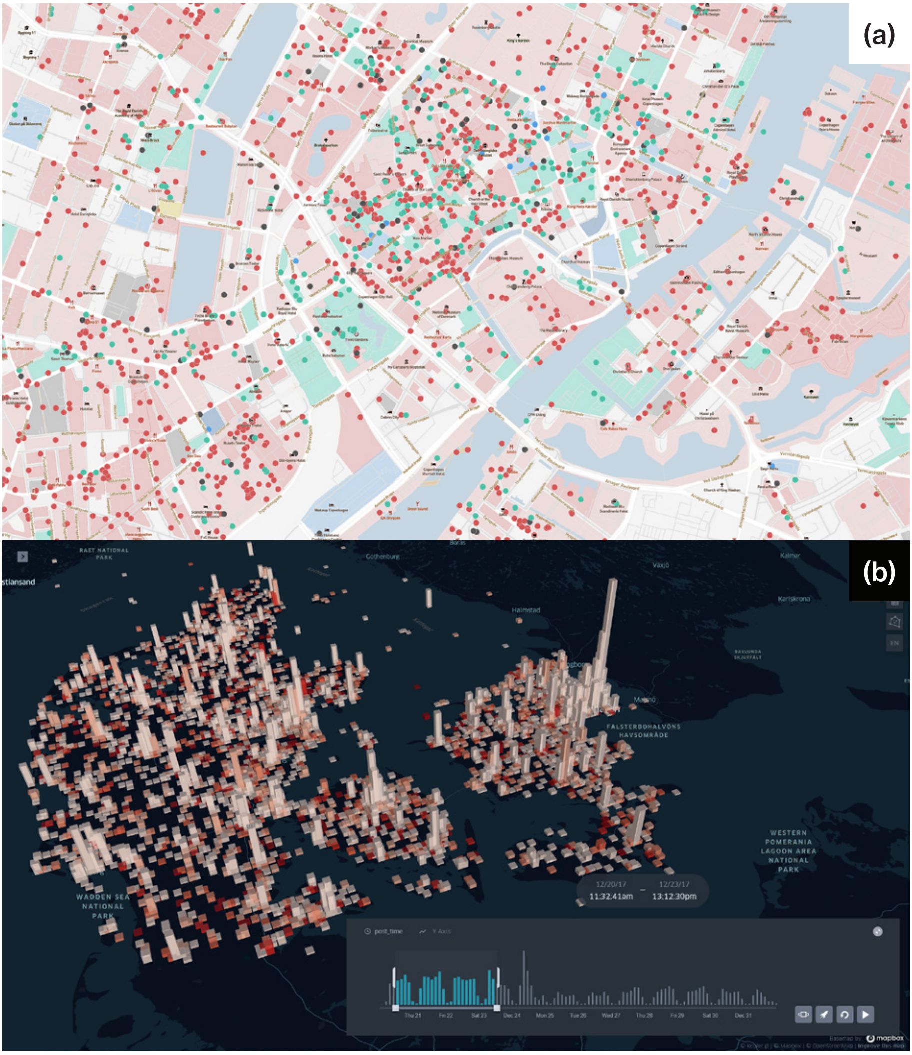


Figure 15. Examples of big data visualizations: (a) a datascape about political diversity in Copenhagen (Madsen et al., 2020); (b) visualization of Christmas greetings on Facebook in Denmark in 2017. Both visualizations are based on data from the Danish Facebook Atlas (Munk and Olesen, 2020). Images reproduced with permission.

The internal order is simply a way to account for the fact that all visualizations have patterns explained by their design (e.g., alignment to axes). In these examples, the internal order are the underlying maps of Copenhagen for Figure 15(a) and Denmark for Figure 15(b). For Figure 15(a), the first layer of the emergent pattern is the presence of dots in certain places, which in this case represent venues or events. The second layer of the emergent pattern is the presence of green patches in the middle of mostly red areas. Here, color indicates the political leaning of the crowd attending the venue (red for leftists, blue for right-liberal, and green for a diverse crowd). In Figure 15(b), the first emergent pattern is the presence of dense bars in urban areas. In the interactive version of the visualization, the second emergent pattern is the general rise of bars at the moment of the Christmas greetings, i.e., 24 December at midnight, which was also visible in the bar chart on the bottom-right. Figures 2 and 5 naturally qualify as big data visualizations, and their main emergent patterns are their clusters. This definition allows us to approach network maps purely as images, regardless of where they come from. This will allow me to propose a model of how one interprets a network map in the absence of any context (cf. subsection "The noema of big data visualization").

THE PRACTICE OF VNA

VISUAL PRACTICES ARE AN ENTRY POINT TO ENGAGE WITH NETWORKS

The most obvious use of network maps is to share knowledge about relational phenomena. Bounegru, Venturini, Gray, and I (2017) identified five ways in which networks are used for journalistic storytelling: (1) exploring associations around single actors, (2) detecting key players, (3) mapping alliances and oppositions, (4) exploring the evolution of associations over time, and (5) revealing hidden ties. Most of these visualizations are small networks where links can be followed individually, but a few involve large complex networks. Network maps are considered one of the archetypes of data visualization (see, e.g., Munzner, 2014). Graphic designers naturally use this format to convey knowledge about relations. In this context, network visualizations are said to be *explanatory*.

The term *explanatory* is classic of graphic design and is sometimes opposed to *exploratory* (see, e.g., Iliinsky and Steele, 2011). Explanatory images are crafted for communication purposes, i.e., to convey a given message. Graphic designers are specifically trained for this task. For instance, they know how to hierarchize visual signals and articulate visual variables to communicate knowledge as clearly as possible. Such images are called *explanatory* because their aim is to convey a message; thus, they explain. I will return to exploratory images shortly.

Journalists rely on explanatory network maps because the visual is a convenient entry point into relational data. I have mentioned how Newman (2018: 1), renowned for his theoretical contributions to NS, has introduced networks from the visual standpoint, as drawings of "points joined together in pairs by lines." Our visual senses are undoubtedly useful when it comes to apprehending the intricate interplay of relations. It is not surprising that we are naturally drawn to them when we need to engage with networks. In "Unblackboxing Gephi,"* Jokubauskaitė and I account for beginners discovering NA by engaging with a visual instrument. One of our interviewees said, for instance, that "through the time of working with [Gephi] you … get to know what it … represents. So it gives you more insight into what it is … that you are working with." We argue that network practices are largely determined by the ease of use offered by tools such as Gephi. We describe Gephi as a distributed laboratory where a specific epistemic subculture (Knorr Cetina, 1999) emerged. We account for the importance of Gephi's ability to produce network maps quickly, even though this was not supposed to be its main purpose (I say it as its main designer, but regardless, the fact is documented in "Force Atlas 2"*). The appetite for a visual engagement with networks is so strong that it shifted the purpose of Gephi.

Visual practices with networks are not always primarily about analyzing, yet I refuse to demarcate VNA from non-analytic visual practices. I have two reasons: the interpretive principles do not differ, and they form a continuum of practices that forms the learning curve that allows beginners to gradually build expertise. Visual network practices encompass monitoring, play, and learning. In a typical monitoring situation, you open a network in a visual tool, such as Gephi, in order to check that the data have no obvious issues: are there nodes and edges in the expected numbers? Are they connected as expected? This practice might seem trivial, but as all data scientists know, data quality is a constant and time-consuming concern. Even though monitoring is quick and approximative, it is a very real part of data practices. Playing and learning are better known network practices, yet they are often disregarded because they do not contribute directly to science. Nevertheless, all experts were once beginners, and I was certainly an enthusiastic amateur who learned by doing—and I am not alone. As a tool maker, I strongly believe in the benefits of playing as part of learning. When Gephi is mentioned on Twitter, it is not necessarily to publicize well-crafted network maps. It is also quite often meant to share the simple joy of engaging with networks: a weird shape, an unexpected result, or just the success of making it work. In the context of Twitter, Gephi users rarely pretend that there is much more to see than a puppy- or octopus-shaped network (Figure 16, on the following pages). However, in other contexts, such as seminars or reports, the circulation of meaningless images has consequences.

STORYLETTING AND THE PERFORMATIVE EFFECTS OF NETWORK MAPS

If storytelling is the art of intentionally building a narrative, then story*letting* is the act of unintentionally letting an inscription tell its own story. I offer this invented term to put a name on a common yet complicated situation. Let me introduce it by an example: a researcher produces network maps during the exploration of a data set. When the time comes to disseminate the findings, these visualizations are no longer necessary. Indeed, the evidence is provided by graph metrics, such as in my preliminary example (Figure 5), yet the researcher features the visualizations in the slides as they provide some imagery to the otherwise unengaging results. In this scenario, the visualizations are featured, for no particular reason, as marketing assets. They are not contextualized, and the audience will probably not be able to read them properly. Nevertheless, they will produce an effect and will a certain story. Rieder and Röhle (2017) call this an epistemic surplus. The important part of this notion is the *unintentional* production of knowledge. Storyletting is the name I give to the practice of circulating that knowledge, a situation that I have observed directly (see Figure 17).

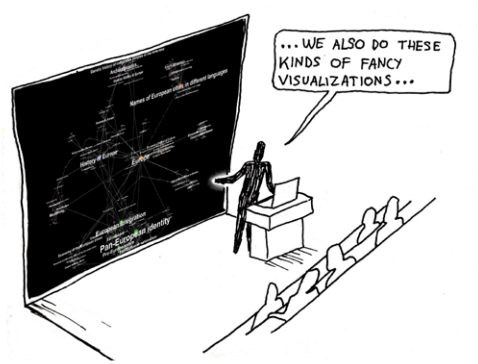
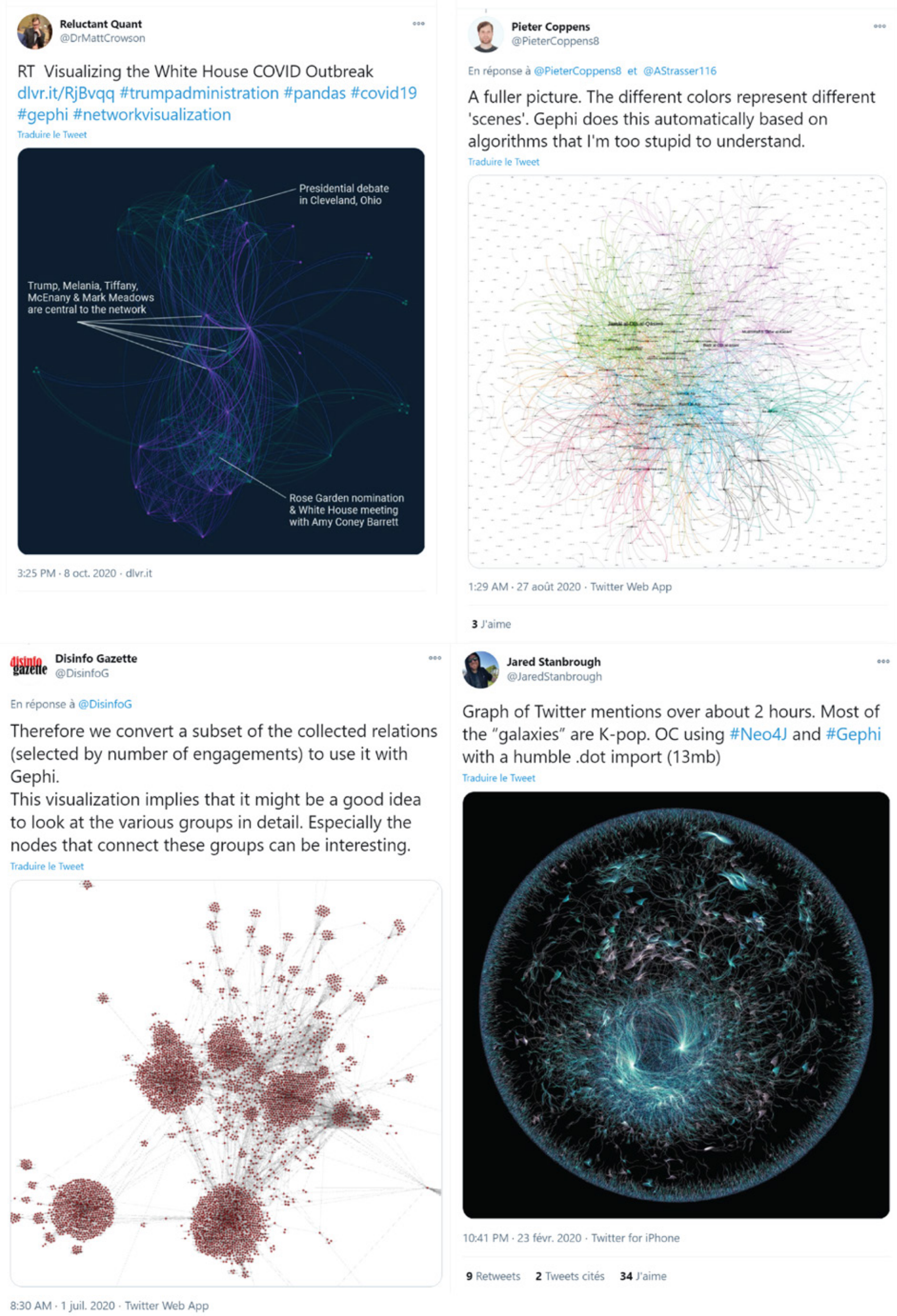
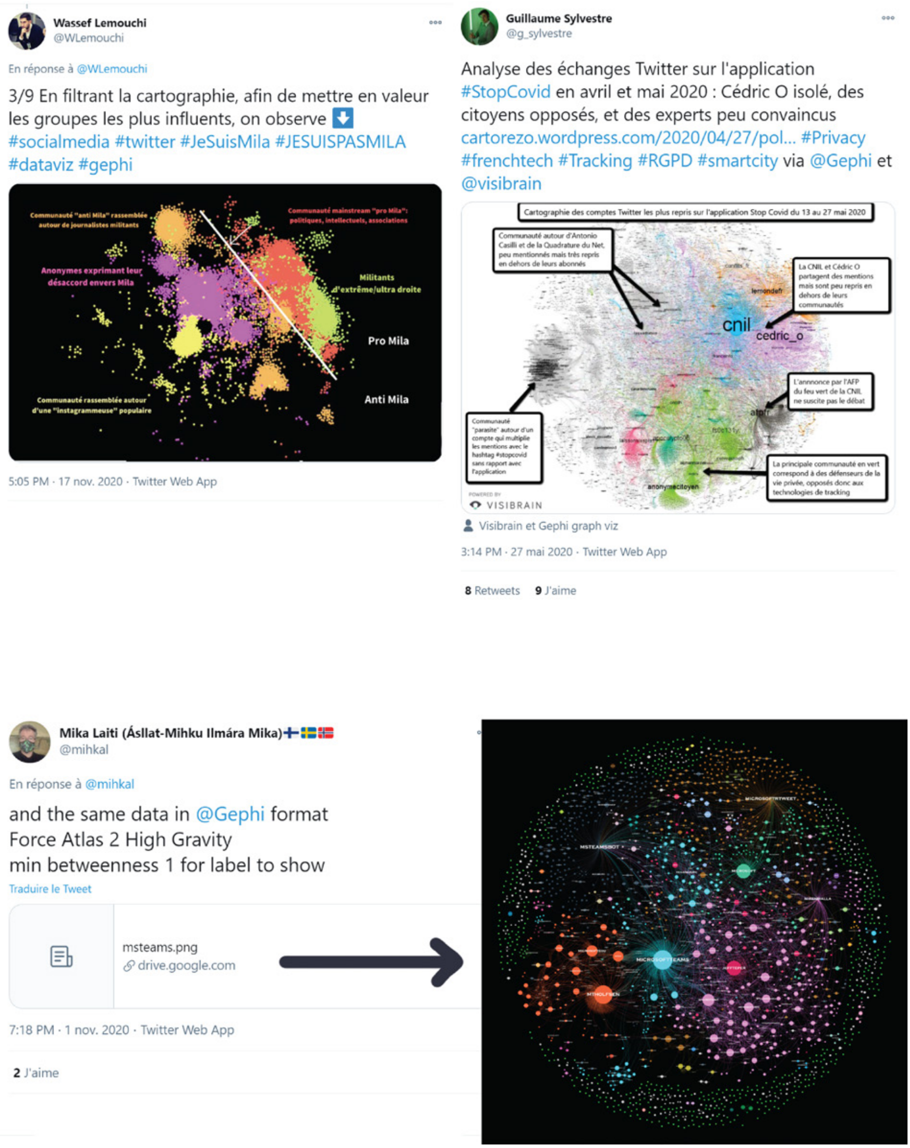


Figure 17. Network maps as an epistemic surplus. This picture represents a situation I witnessed. A scholar presents a screenshot of their exploration process, featuring a network. They do not interpret it and, instead, frame it as a "fancy visualization." Here, I used a screenshot of my own process during the exploration of the network of Figure 5.

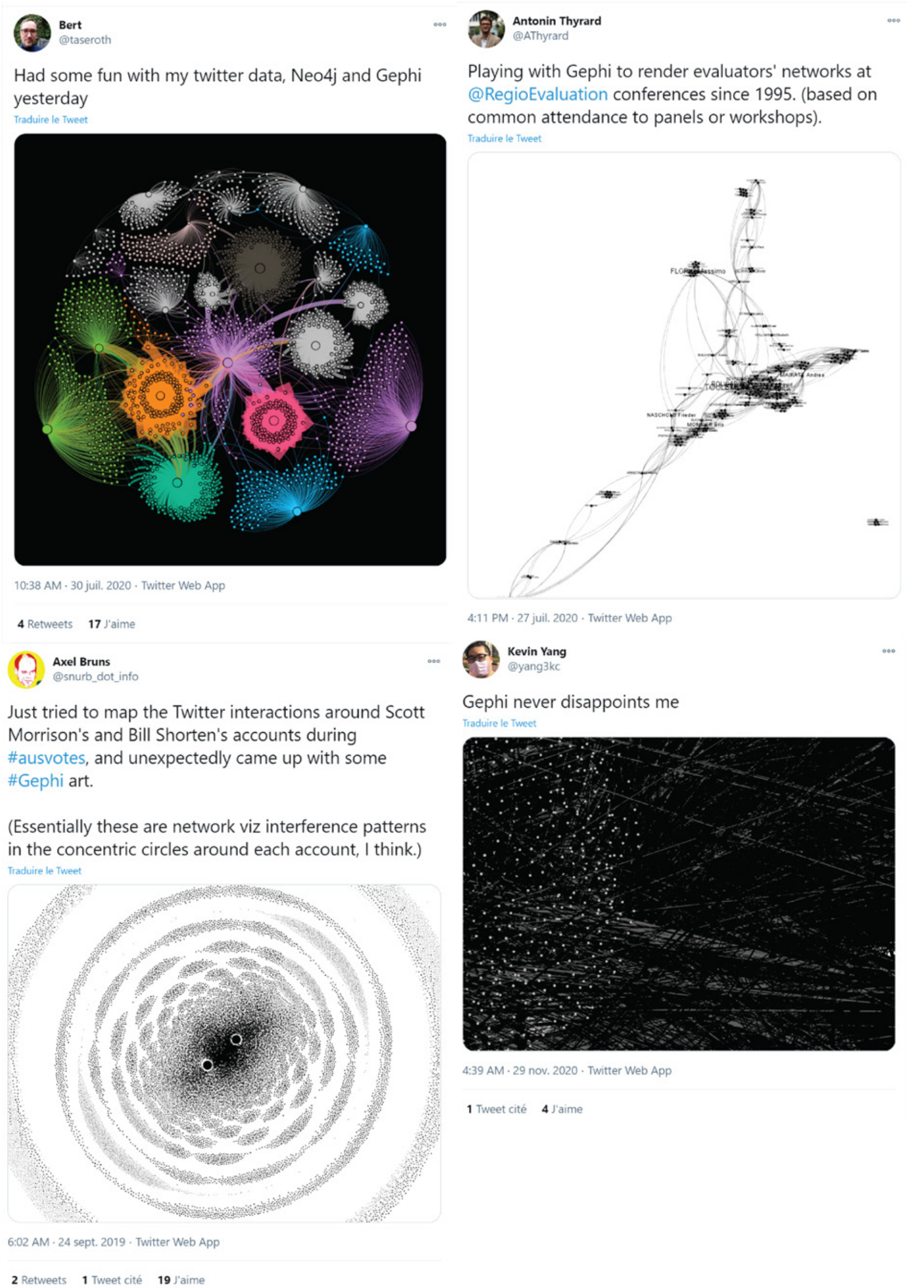
Storyletting also happens in academic publications. Foucault Welles and Meirelles (2015) provide a complete and nuanced account of the circulation of



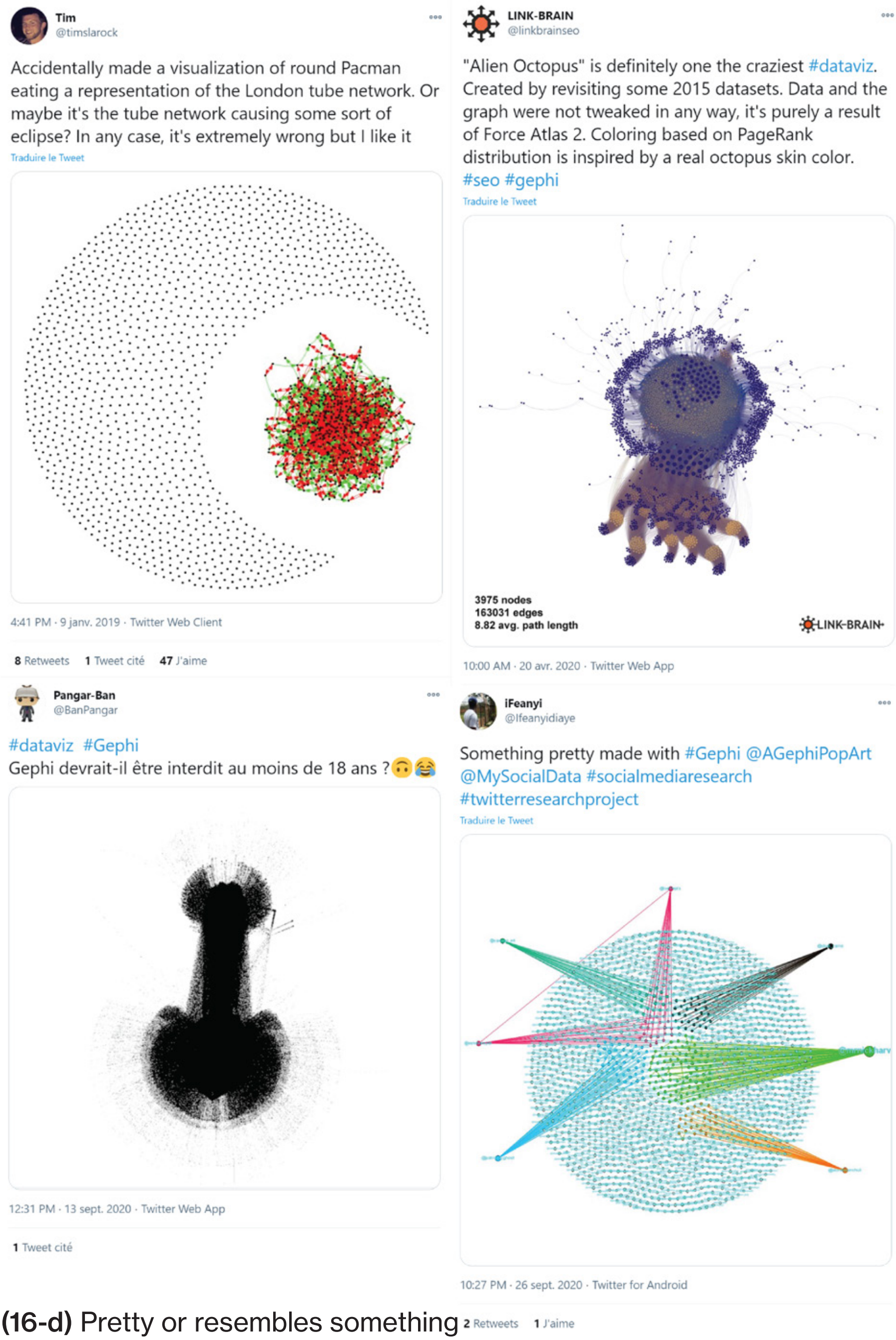
(16-a) Sharing an analysis or the representation of a phenomenon



(16-b) Sharing an analysis or the representation of a phenomenon



(16-c) Playing with Gephi, curiosities, or glitches



(16-d) Pretty or resembles something

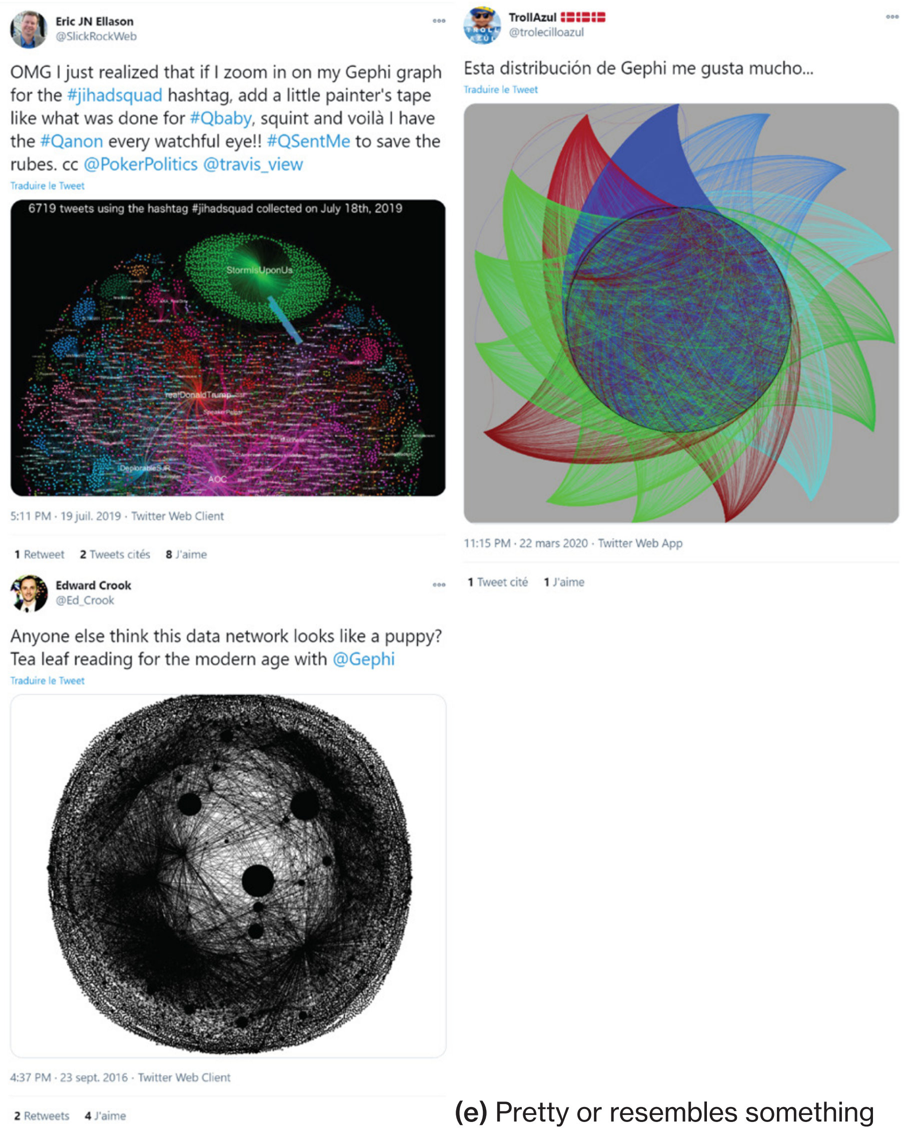


Figure 16. Examples of network maps produced with Gephi, as tweeted by their authors: (a) and (b) Network maps tweeted to share an analysis or the representation of a phenomenon, where contextual information varies (annotations, methodology, algorithms and their setting; (c) Network maps tweeted as examples of playing with Gephi or as curiosities or glitches; (d) and (e) Network maps tweeted because they are pretty or look like something. Reproduced with permission.

Adamic and Glance's (2005) network map of the US blogosphere (Figure 2). The figure displays two densely packed groups of nodes, one blue and one red. The picture is profoundly aligned with the message of the paper, which is that the political blogosphere is divided. However, is this the message of the picture? The *situatedness* of this image depends, of course, on its context. The paper measures polarization by counting the links and calculating densities, not by interpreting the picture. The caption is important; it reads as such: "**Community structure of political blogs** (expanded set), shown [utilizing] the GUESS visualization and analysis tool. The colors reflect political orientation, red for conservative, and blue for liberal. Orange links go from liberal to conservative, and purple ones from conservative to liberal. The size of each blog reflects the number of other blogs that link to it" (Adamic and Glance, 2005, emphasis added). The caption partially builds on self-evidence, as it assumes that the community structure is simply visible, but it does not invisibilize the mediation. The tool is mentioned, and the authors do not pretend that the picture shows political polarization itself—it is up to the reader to figure out what the community structure is. The caption, and more generally the paper, grounds that knowledge. However, this context was challenged when the image circulated in other places.

> *The reproduction of the blogosphere visualization in* Science *as well as in the book* Connected *… likely contributed to its wide dissemination, as evidenced by reproductions in hundreds of articles and blog posts written since 2009, including articles in several languages. … Strikingly, many of the reproductions omitted a caption describing the image. It is not simply that the original caption was not reproduced, rather, in several instances in popular writing, the reproduction of the blogosphere visualization lacked any caption at all. Without a caption, the image fully realized its transformation from an illustration of scientific process, to evidence of scientific results, and finally to an icon emblematic of the whole topic of American politics, or more specifically, to the political division in the United States. (Foucault Welles and Meirelles, 2015: 18)*

The picture started telling its own story while circulating, a story about the polarization of US politics. I do not point my finger at Adamic and Glance (2005) but at the authors who peeled the image of its context (Foucault Welles and Meirelles, 2015, provide a list).

At the same time as Foucault Welles and Meirelles, Andris et al. (2015) published an article on US political polarization, making a similar argument as Adamic and Glance's (2005) a decade earlier but using data on the votes of the U.S. House of Representatives from 1949–2012. The first two figures, reproduced in Figure 18 of this dissertation, stand out. The first shows two similar curves that diverge over time, while the second shows two clusters, one blue, one red, that separate over time. Surprisingly, the two separating curves do not represent the Democrats and Republicans; they represent the cross-party and same-party probability of agreement in terms of votes. The networks of Figure 2 (see Figure 18) represent the parties, and the weighted links represent the number of vote agreements. The caption mentions a force-directed layout. In both cases, the visual message is that of an increasing message, but does it count as evidence? The curves illustrate simple numbers that constitute a classic piece of evidence: cross-party alignment drops, while the same-party alignment rises. The networks, however, represent a divide that is not easily interpreted. There are too many links, and we cannot count them. The node placement remains, but explaining how it relates to the links requires understanding the layout algorithm. The networks illustrate more than they provide evidence regarding the main

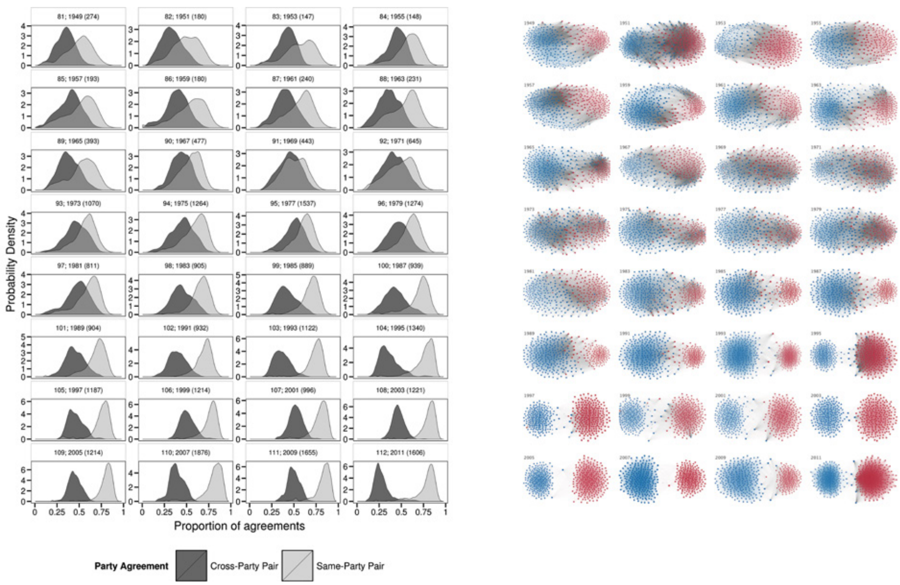


Figure 18. Two figures from Andris et al. (2015) on the polarization of votes in the US House of Representatives. Left: Figure 1, titled "Probability density functions of same-party and cross-party pairs over time". Right: Figure 2, titled "Division of Democrat and Republican Party members over time." © 2015 Andris et al. (2015). This work is licensed under CC-BY.

claim of the paper. However, the titles tell another story. The title of the curves figure is technical and provides the necessary reading context: "Probability density functions of same-party and cross-party pairs over time." On the contrary, the network figure provides no context, instead conflating the representation with the represented: "Division of Democrat and Republican Party members over time." Here, the networks are presented as self-evident. The paper arguably provides enough context, but like for Adamic and Glance (2005), it is the network figure that circulated—and mostly without context.[14] Network maps are also cultural artifacts that participate in a wider, non-academic culture that retroactively influences network practices, notably of beginners (we develop this point in "Unblackboxing Gephi"*).

EXPLORATORY DATA ANALYSIS

When it comes to engaging with networks as a one-person activity, VNA is most often about exploration. I have addressed the distinction between *explanatory* and *exploratory*. One cannot optimize for the clarity of a message without having that message in the first place. Exploratory visualizations have meanings but no preexisting message to convey. Although they are constructed, the goals of their construction are different. For instance, we refrain from sacrificing visual signals for clarity because such details might be important. In fact, exploratory images tend to be quite raw. Gephi was designed primarily to support exploration, even though it has been used extensively to produce explanatory visualizations.

I will make use of another demarcation, this time between *exploratory* and *confirmatory*, theorized by Tukey (1977). EDA "is a well-established tradition based primarily on the philosophical and methodological work of John Tukey… [He] fought what he perceived as an imbalance in efforts aimed at understanding data from a hypothesis-testing or confirmatory data analysis (CDA) mode while

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14 A few web pages where only the network figure is featured, never containing caption:
https://www.washingtonpost.com/news/wonk/wp/2015/04/23/a-stunning-visualization-of-our-divided-congress/
https://www.vox.com/2015/4/23/8485443/polarization-congress-visualization
https://towardsdatascience.com/analyzing-political-polarization-on-twitter-engagement-graphs-aa0614ed1361
https://urban-plains.com/the-polarized-states-of-america/
Similarly, on Twitter:
https://twitter.com/nachristakis/status/591547410092011520
https://twitter.com/simongerman600/status/1321738809382416385
(all URLs accessed 05 November 2020).

neglecting techniques that would aid in understanding of data more broadly" (Behrens and Yu, 2003: 33). In a nutshell, EDA aims to generate hypotheses, as opposed to CDA, which aims to assess them. Exploration and confirmation are distinct situations. They do not happen at the same stage or play the same role in a research design, and they have different goals. Remarkably, however, they often use the same tools. The question of the apparatus involved was crucial to Tukey, who argued that confirmatory tools were not necessarily adapted to exploring data, particularly in relation to the visual. "The greatest value of a picture is when it forces us to notice what we never expected to see" (1977: vi).

Tukey defended exploration for its intrinsic values, not as an inferior version of confirmatory analysis. For him, it was "[f]ar better an approximate answer to the *right* question, which is often vague, than an *exact* answer to the wrong question, which can always be made precise" (Tukey, 1962: 13). As I took charge of Gephi's design, I adopted this perspective. It suited my situation, my needs. Within the "e-Diasporas Atlas" project (Diminescu, 2012), we harvested networks of websites, but we did not have many points of comparison. We needed to make up our own minds without the possibility of relying on existing studies of networks of migrant websites, and the visual was absolutely key to our endeavor. I designed Gephi primarily to support exploration. Not even the map-making features were designed to produce explanatory visualizations for other people: we just wanted to print and annotate our own networks and to discuss and understand them collectively (Figure 19). The computers were slow, the monitors had poor resolutions, and the paper was (and probably still is) a superior support to handle large (static) data sets. Gephi was designed as an exploratory device.

The e-Diasporas project produced a large series of papers examining the web of migrants. These papers are presented on the project website (Diminescu et al., 2012). They often included network maps, always accompanied by explanations. NA is a complement to many other strategies: field work, statistical analysis, etc. The project also produced a set of posters (Figure 20) accompanied by a smartphone app capable of providing video explanations by the authors of each network map. This work was no longer exploratory. It was aimed at disseminating the results and was now explanatory. Each network map was associated with findings, explanations, and statistical figures. The object was co-designed with the design studio Incandescence. Many labels were removed to limit visual cluttering; the colors were reduced to a minimum; and many other semiotic adjustments were made. Incandescence's lead designer pushed strongly for the removal

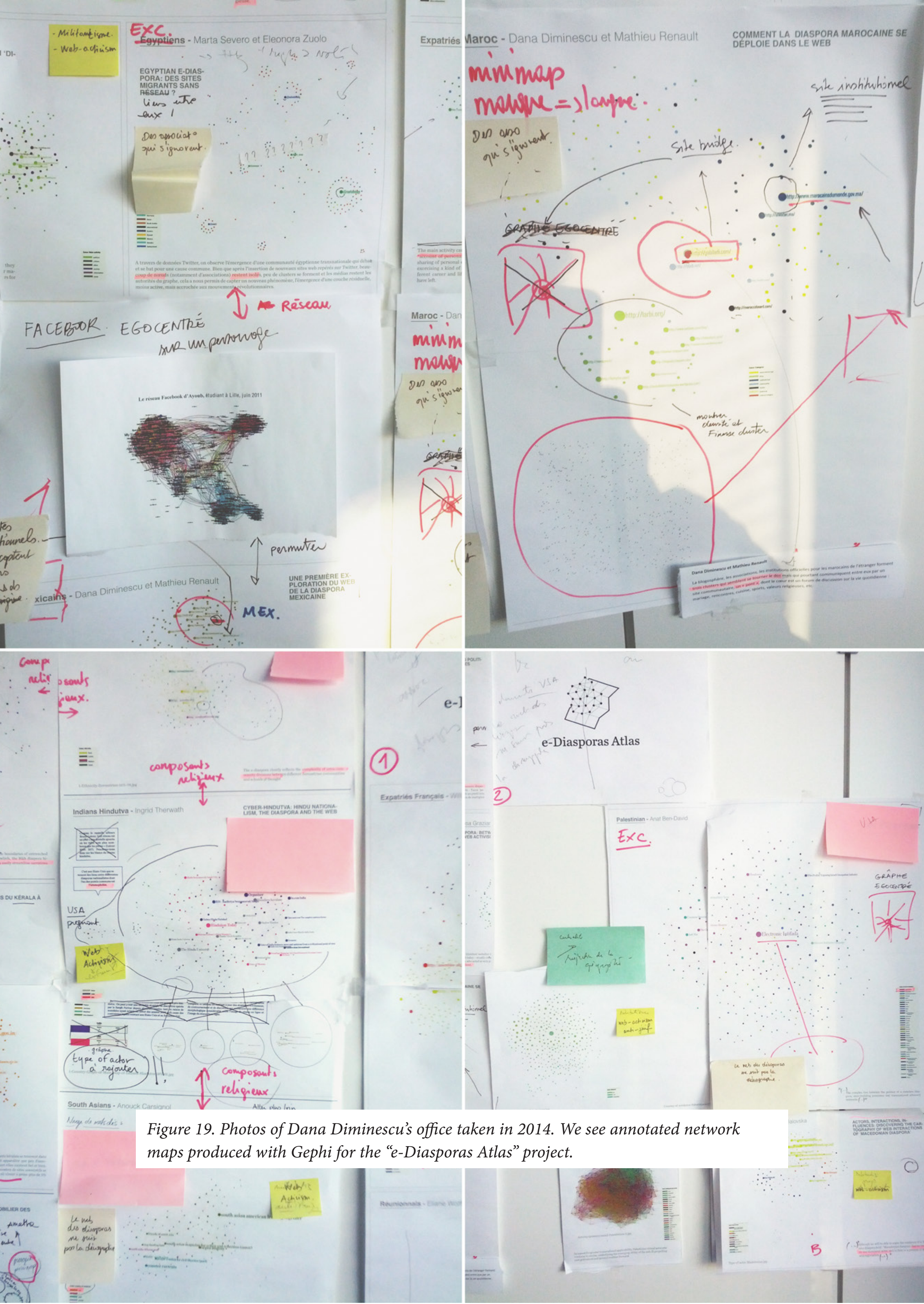


Figure 19. Photos of Dana Diminescu's office taken in 2014. We see annotated network maps produced with Gephi for the "e-Diasporas Atlas" project.

Figure 20. The e-Diasporas Atlas itself, a set of posters with network maps redesigned in collaboration with the design studio Incandescence. A companion app provides explanations on each case, also accessible on a website (Diminescu et al., 2012).

or reduction of the number of edges (lines), but I resisted the idea. Networks are all about links, I thought, so we must see them. Today, I think his suggestion was sound. Indeed, the edges were already represented in the node placement. Some authors do advocate it (e.g., Noack, 2007b). I will return to this point, but let me remark that this project was successively exploratory, confirmatory, and explanatory. The different dimensions of VNA coexisted, which is the norm rather than the exception.

Munk (2021) documented his network exploration process, which is uncommon, in a book chapter on Facebook users' culinary discourse. He reconstructed annotated visualizations illustrating the hypotheses generated during his engagement with the data as well as the methodological notes of his process, for instance, the settings of the algorithms used (Figure 21). The visual style of these images (screenshots with manual writing) conveyed the temporariness of exploratory visualizations; indeed, their purpose was to advance the inquiry, not to provide evidence to an audience.

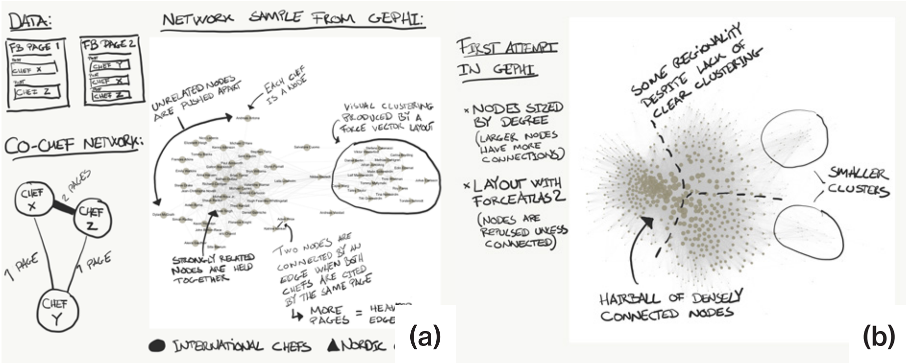


Figure 21. Annotated network visualizations produced during the exploratory analysis of a corpus of chefs mentioned on Facebook (Munk, 2021). Reproduced with permission.

In "Visual Network Exploration for Data Journalists,"* we provide another example. The figures 20.3 to 20.7 in the paper show a series of views that can be obtained in the exploration phase, although they had to be adapted to the context of a book chapter (Figure 22(a)). The figure 20.12, by contrast, is explanatory and does not include a network map (Figure 22(b)). In the example we provide, we account for the exploratory steps that are usually hidden. This is, of course, because we aimed to equip data journalists and not just communicate findings. If we look at academic publications citing Gephi, we rarely see a mention of exploration. However, if we observe the practices of scholars directly, as in "Unblackboxing Gephi"* (see also Van Geenen, 2020, for an autoethnographic account), we see that exploration features almost exclusively. EDA is one of these widespread scientific practices that is almost entirely expunged from publications. For good reason, yes, but let us not forget that, when our goal is to provide evidence, we spend more time cleaning and exploring data than unfolding the nice analytical strategies that we showcase in our papers. Many vagaries occur before we even have a result to share. Thus, exploration is a more common practice than it appears.

CRITIQUING THE VISUAL POWER OF NETWORKS

In this section, I argue that the criticism of network maps from the social sciences and humanities is largely due to their ability to invisibilize the mediations they involve. Network maps do not make their *situation* accessible in the sense of Haraway (1988). A crucial point of criticism is the use that the rhetoric of big data makes of the self-evidence of network maps. I argue that we can mitigate this instrumentalization through normative interventions but that network maps have material–semiotic features that inevitably favor that rhetoric. I characterize

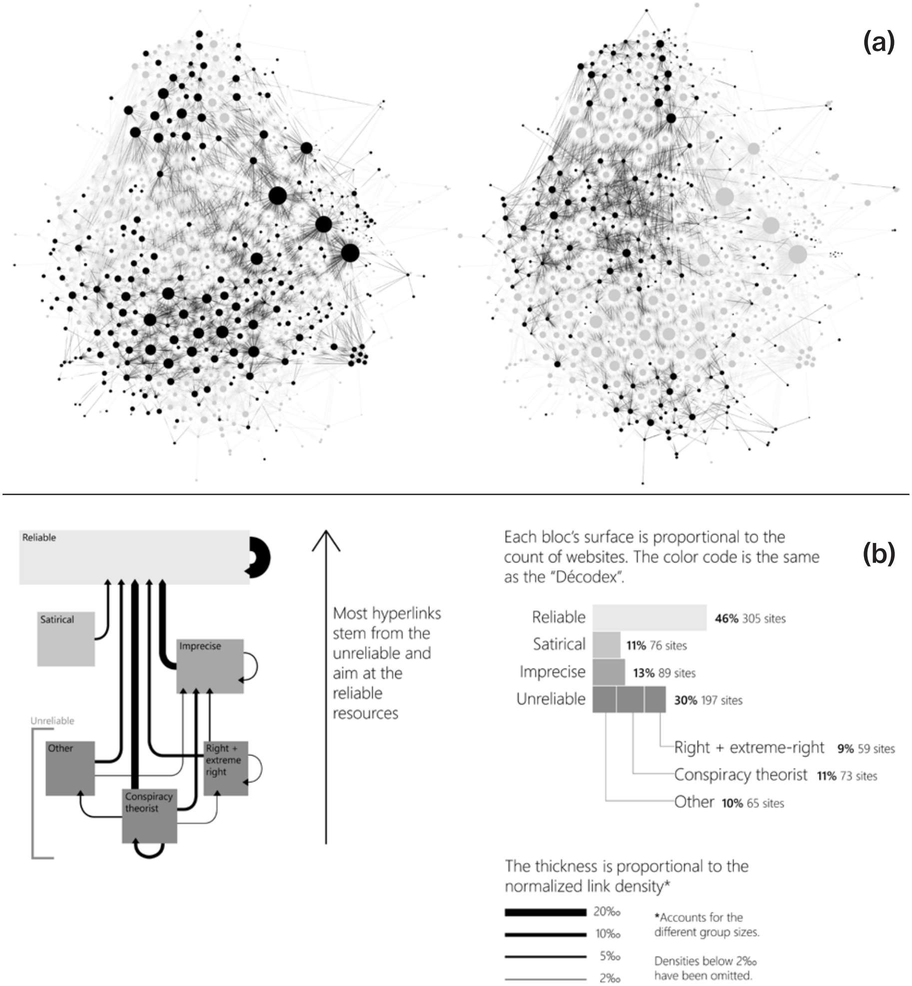


Figure 22. Thumbnails of two figures from "Visual Network Exploration for Data Journalists": (a) an exploratory visualization; (b) an explanatory visualization. The latter does not include a network map.*

these features as the *noema of big data visualization*, which means that "there is an order to this chaos." I contend that the noema is the source of the self-evidence effect and that we can only mitigate it.

Let me start with a first-hand account of the visual power of networks. In "Thinking Through the Databody," Munk, Madsen, and I (2019) narrate a data sprint (a workshop with data scientists, designers, and domain experts) that we co-organized with the Royal Danish Theater (RDT). We observed that network maps were interpreted by domains with a strong confirmation bias. In this particular situation, the "databody" (the network visualization) was unable to oppose resistance to the domain experts' preconceived ideas and preference for agreement.

> *The domain experts from the RDT were given [a network map] annotated with labels so that readers could easily identify which posts belonged to which Facebook page. In this design of the experimental setting, the domain experts had no problems drawing attention to the clusters that clearly verified their existing beliefs about their own organization and their users. For instance, knowing that the audience interested in solo dancers have quite idiosyncratic interests, they pointed to an isolated cluster and concluded: "Yeah, that's typical of the soloist's audience – they are very loyal." Similarly, knowing that two ensembles called Røde Rum (The Red Room) and Eventministriet work with stage plays in the same way, they pointed to two closely overlapping clusters and concluded: "That makes sense because Røde Rum and Eventministriet work intimately together." The same was true for posts acting as bridging nodes between two clusters. Seeing that one of these bridging nodes represented a post about a recent flea market held by the costume department there was immediate agreement: "Look, the flea market held by the costume people attracted quite different user-groups – that makes sense." Similarly, when learning that the nodes towards the centre of the network represented posts from the experimental Corpus ensemble: "Of course, Corpus is the one ballet ensemble that is also attracting interest from people interested in stage plays." We can interpret this way of interacting with the databody as taking place in a submissive or docile setting that does not obstruct the participants' preference for agreement. … The network makes sense to the domain experts because it either fits their preconceived ideas about their own institution, or because these ideas are sufficiently vague to be easily fitted to the network.*

THE STS CRITICISM OF NETWORK MAPS

Within the social sciences and humanities, network maps are often criticized from the standpoint of STS. NA was used in STS following pioneering work by Callon et al. (1986) on co-word analysis. Cambrosio et al. (2020) retraced the history of network analysis within STS (see also "Actor-Network vs. Network

Analysis vs. Digital Networks"*) and remarked that "network mapping comes with built-in epistemological models that are not necessarily compatible with STS research agendas," notably "to capture the dynamics of actor-networks" (p. 1020). Similarly, Munk (2018) argued that network maps do not just improve the exercise of controversy mapping but transform it; thus, we need to be critical about the mediation they perform. In "Unblackboxing Gephi,"* Jokubauskaitė and I provide an overview of the criticism more generally derived from Haraway's (1988) feminist STS. It is directed at big data visualization, network maps, and the instruments that produce them. The arguments vary, but always point to a problem with transparency. In short, network maps make you forget the mediations involved; they have the dangerous power to appear self-evident—due to a semiotic effect and/or the rhetoric of big data. For some, visualizations "are a kind of intellectual Trojan horse" (Drucker, 2014: 125), "a vehicle … for [the] claimed self-evidence [of the data]" (Ruppert and Scheel, 2019: 10). For others, "the problem … comes from the fact that tools such as Gephi have made network analysis accessible to broad audiences that happily produce network diagrams without having acquired robust understanding of the concepts and techniques the software mobilizes" (Rieder and Röhle, 2017: 118). As Campagnolo (2020: 45) argues, the "epistemological preferences [of network mapping] remain concealed under a guise of completeness. Networks become automatically complete with what is available in the data."

These criticisms often draw on Haraway's (1988) "Situated Knowledges" and her early warning against self-evident representations. "There is no unmediated photograph or passive camera obscura in scientific accounts of bodies and machines" (p. 583). This "god trick of seeing everything from nowhere," she writes, can claim "the power to see and not be seen, to represent while escaping representation" (p. 581). There is a point of framing big data visualizations, including network maps, as self-evident: in the (apparent) absence of any mediation, there is nothing to criticize. Indeed, as no mediation is perfect, all mediations are unfaithful in their own ways. If objectivity is understood as the fidelity of a scientific account, then the absence of mediation is its ideal. Unmediated visualizations become the standard against which the other visualizations can be assessed. Haraway highlights this as the "power … to represent while escaping representation" (p. 581). The point of "Situated Knowledges" is precisely to assert that no scientific account is unmediated, to denounce the representations that pretend otherwise, and to reclaim the power they hold. Network maps, and more generally the visualizations showcased in a big data situation, are precisely seen to have a similar influence. It is suspected that they pose as unmediated representations, "promote and transport innovation strategies, and serve as important tactics in struggles over influence, agendas, budgets and different forms of capital in the transnational field of statistics" (Ruppert and Scheel, 2019: 17). Similarly, Munk, Madsen, and I (2019) have observed that network maps offer no resistance to non-experts who find in them the confirmation of their preconceived ideas.

As a tool maker, I face this criticism in two ways. First, do network tools *enable* instrumentalization in the rhetoric of big data? For example, do they "enact new realities such as populations" (Ruppert and Scheel, 2019)? Second, do network tools *cause* a dismissal of the mediations involved? Is there something, in their material–semiotic constitution, that actively conceals the context of their fabricated knowledge? Here, I aim to contrast two ways in which the responsibility of network visualization can be addressed: one passive (docility to instrumentalization) and the other active (material–semiotic influence). I admit that this dichotomy is overly artificial, but it helps me as a tool maker because it suggests two different avenues of action: the culture around the apparatus or the apparatus itself. I will argue in the next section that *big data visualizations* (as characterized in the first section of this chapter) actively contribute to the self-evidence effect.

To mitigate the instrumentalization of network maps in the rhetoric of big data, I propose a normative approach. I acknowledge that this instrumentalization exists and that *we* cannot prevent it entirely. However, *we* can refrain from incentivizing it whenever possible. This "we" refers to the collective of tool makers and users co-designing the apparatus of network visualization, including cultural artifacts (e.g., documentation, tutorials, Facebook discussions). As narrated in "Unblackboxing Gephi,"* beginners are more oblivious to the methodology underlying their use of Gephi, and even experienced users rely on shortcuts when they analyze networks in time-restricted environments. The lack of awareness of the methodology becomes a problem when the instrument makes outputting images easy. Visualizations produced by people who cannot properly interpret them constitute an "epistemic surplus" (Rieder and Röhle, 2017), knowledge that is unintentionally produced. Users producing these images for themselves, for instance, to discover the instrument, are not doing anything wrong. However, circulating these images is problematic because the dismissal of the methodology leaves only one way to interpret them: self-evidence. We can raise awareness about the consequences of circulating uninterpreted network maps, make it more difficult to output images in Gephi, and incentivize users to interpret their images properly. As VNA is mainly a practice and not a theory, researchers cannot write an interpretation for sharing with others. I think that it is worth formalizing a process for interpreting network maps and sharing this interpretation. In "Translating Networks,"* Grandjean and I propose a correspondence between visual features and statistical metrics, and my co-authors and I document the algorithm "Force Atlas 2"*; however, these were preliminary steps. The difficult problem is to formalize an interpretation of the layout. I highlight historical reasons for the absence of a compelling theory in the next chapter and contribute with two interventions in Chapter 5.

Active responsibility begs the question of whether some material–semiotic features of visualization can, by themselves, invisibilize the mediation. If self-evidence is the symptom, what is the disorder? As an element of the answer, I offer a simple semiotic model of *big data visualizations*. I argue that they convey a meaning that favors the rhetoric of big data but does not depend on it. I refer to this meaning as the *noema* of big data visualization, following the semiotics of Barthes (1981). In short, the noema roots the self-evidence effect in the visualization's ability to manifest emergent patterns. The inevitability of this manifestation is crucial to the critical project of improving the instruments of VNA because it tells us that the self-evidence effect, i.e., Haraway's (1988) "god trick of seeing everything from nowhere," cannot be entirely avoided. It is an integral part of the interpretive process of network maps and big data visualization more generally.

THE NOEMA OF BIG DATA VISUALIZATION[15]

Here, I argue that the noema of big data visualization is that "there is an order to that chaos." Before I get to what a noema is and why it is as it is, I will facilitate my explanations by presenting the purpose of this idea.

My motivation is to defend the visual power of network maps as something that is real, in the sense that it can influence readers even in the absence of rhetoric (active responsibility). Beyond that, I contend that this visual power is legitimate. I want to resist the idea that big data visualization is fake, that it only works thanks to rhetorical games in the politics of method. I want to stress that big data visualizations actually mean something; even in the absence of rhetoric, they mean that *there is an order to that chaos*. It would be a mistake to believe that

15 This section draws on an essay I self-published on my research blog titled "Seeking the noema of big data visualization." Although less refined, it provides additional information. https://reticular.hypotheses.org/1647 the imagery of big data is convincing only because of rhetorical effects. It would downplay the problem. This point is important because, as Jokubauskaitė and I argue in "Unblackboxing Gephi"* following Latour's (1986) observations on "immutable mobiles," the circulation of these images has an effect on its own. It is not only used rhetorically; it enacts a rhetoric.

What is a noema

I draw inspiration from the French semiotician Roland Barthes. In his book *Camera Lucida* (1981), he inquires into the essence of photography from a phenomenological and personal standpoint, reflecting on images of his recently deceased mother. Photography is an excellent landmark to reflect on self-evidence. A photograph is generally held to be true, and as such, it is self-evident. However, we know that it is also fake, that it is not really what it pictures. Barthes asks the important question: why do we hold to be true what we know to be an illusion? Barthes articulates how the sincerity of his emotions derives from a treacherous image. Despite his mother posing for the photographer, despite the artificial setting, despite the photographer's touch, the photograph is the trace of a moment that actually happened. Indeed, the trace of this moment was transported materially to the viewer. Despite the fabrication, it has been. For Barthes, this is the essence of a photographic image. He calls it the photographic noema: *that has been*, "ça a été."

The noema is a phenomenological notion introduced by Husserl (Føllesdal, 1969), which Barthes has used in a pretty liberal way. As there is a protracted controversy on its exact meaning, which does not matter much here, I stick to Barthes' (1981) loose usage. One may understand it as "essence," but Barthes' inquiry into the meaning of images is phenomenological, not essentialist.

The noema is a material–semiotic feature of a certain class of images. The noema of photography is semiotic because we recognize familiar figures, and it is material because the (relative) fidelity of the image derives from the mechanical chain of reproduction from the subject to the film and to the paper or screen. Of course, today's digital era has changed the situation, and Barthes' noema needs an actualization, which is just saying that the meaning of images has changed. Regarding the noema of the digital, Bachimont (2004) has proposed that *that has been manipulated*, "ça a été manipulé."

The noema does for Barthes two interesting things. First, it gives a single point of origin for multiple interpretations. The same image may mean different things to different people, and these meanings can be unpacked by starting from the same underlying assumption. Second, the noema is specific to photography. It defines its particular semiotic character. The noema I propose does for us similar things. It allows us to unpack the rhetoric of big data as well as its criticism, and it defines the specific semiotic character of big data visualization.

Why big data visualizations tell that "there is an order to that chaos"

As I argued earlier, big data visualization is defined by a proliferation of signs and the presence of patterns. The noema, *there is an order to that chaos*, derives from the interplay between these two properties.

The proliferation of signs has several effects. First, it overwhelms the reader. The eye does not know where to land—the image requires an effort. Second, it makes it clear that these signs have not been placed manually to convey a specific message. A human would not have taken the time to place them, so the placement has to reflect some attribute of the data. Third, assuming that the image is intentional (i.e., not a random screenshot illustrating a process), it tells that it is open to interpretation. Indeed, if there was a clear message to convey, the data would have been further reduced to remove unnecessary visual noise. In short, the proliferation of signs speaks of "chaos," "raw data," and "potential for interpretation."

The presence of patterns, often highlighted in the title or caption, speaks of "order." Of course, we must exclude the structures that are trivially explained by the construction of the image, for instance, the axes of a scatter plot. Most visualizations contain signs that have a direct meaning, but the patterns I mention here are those emerging from the accumulation of signs. Importantly, the meaning and shape of the patterns may well be undefined, provided that one can agree on their presence. For instance, we may agree on the presence of visual clusters but disagree on where they are or how many. It does not matter that the "order" is unspecified, as long as its presence is assured. The material–semiotic feature of *patterns in a proliferation of signs* specifically implies that *there is an order to that chaos.*

Using the noema to unpack the meaning of a big data visualization

Crucially, the noema does not tell *which* order is present in the visualization. It just tells that *some order* is present. Anyone can have their own reading.

Therefore, the noema does not determine how to read the image; it prompts an interpretive inquiry. It provides a common premise to the different possible interpretations. The purpose of the concept of the noema is to make it clear that the presence of an interpretable order is *meant* by the visualization and not imported from some rhetoric such as that of big data. Different kinds of rhetoric can leverage the presence of an interpretable order, but none of them brought it into existence in the first place.

It is also important to understand that the noema can be wrong—the same way that a photograph can represent false things and still mean *that has been*. The noema of big data visualization, by suggesting the presence of an order, triggers an inquiry to analyze this order. This investigation is an active pattern recognition process that is never guaranteed to succeed. It is not given that a consistent interpretation will be found and, even then, that this interpretation will be legitimate. However, even when the inquiry fails, the noema has played its part by prompting it. I have defined the noema after characterizing big data visualizations, but it can be understood the other way around: **big data visualizations are images that prompt a visual inquiry about the meaning of emergent patterns.**

I offer three examples to illustrate how this visual inquiry is prompted: a network map where a meaning can be found, and conversely, two images where the inquiry fails. The network map, presented in Figure 23 comes from "Visual Network Exploration for Data Journalists."* I suggest you take a minute or so to look at it before moving on to my proposed reading.

In this paragraph, I deconstruct my reading of the image, assuming I have minimal knowledge about it: I know that the dots represent websites, that the lines represent hyperlinks, and that only some of the labels have been displayed. There are too many dots to count, and only a few of them have a label: only the biggest, it seems. I notice some known labels, such as YouTube, Twitter, and Facebook. I wonder why all these dots are displayed, especially since most labels are not displayed. It must say something about the displayed labels. It might be about how they are connected, but there are so many lines that I cannot really follow them individually (why show them?). It might also be about the placement of the dots. Most dots are either at the top or bottom. The labels tend to be displayed in three areas, which are also where I see the biggest dots. The part on the right has a few big dots and not many small ones. Now, if I look at the labels, I see that I can make three different groups: the English-speaking media on top, the

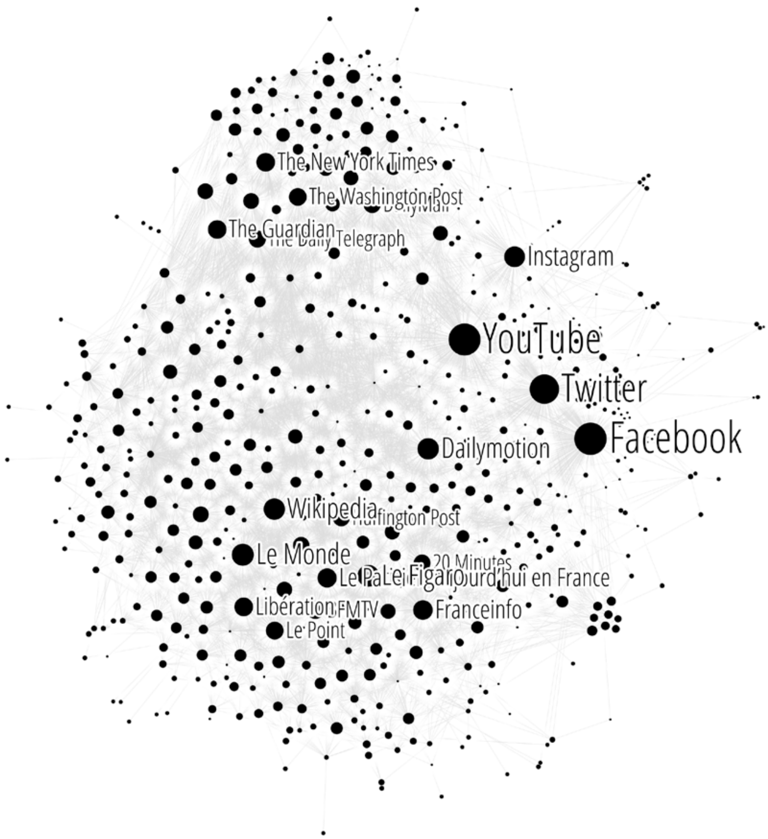


Figure 23. The Décodex network spatialized by Force Atlas 2, from "Visual Network Exploration for Data Journalists." The proliferation of signs (many nodes and edges) and emergent patterns (English-speaking media on top, French-speaking media at the bottom, social media on the right) make it a big data visualization.*

French-speaking media at the bottom, and social media on the right. The dots, representing websites, seem to gather in a certain way. From there, understanding what it means requires more information.

This reading is debatable, but I think we can agree that it is reasonable in a scientific context where the reader is acculturated to data visualization. Here, I assumed zero knowledge on how the nodes have been placed (the layout algorithm). Quite a considerable amount of knowledge can still be obtained from the image. The visual inquiry ends in a hypothesis on how the dots are gathered. Of course, we provide the necessary context in the paper.

My second example is presented in Figure 24. I suggest you ignore the caption and try guessing what it represents.

Here is my reading, assuming minimal knowledge. This hexagonal layout reminds me of two kinds of maps: strategy game maps and self-organizing maps (Kohonen, 1982), an unsupervised machine-learning technique of dimensionality reduction that has points in common with network maps. If the hexagonal tiling is implicitly part of the design rules of the image, the emergent pattern consists of colored patches that remind me of continents or territories of some sort. Tiles of the same color clearly tend to aggregate, and the patch borders are not clear-cut but ripped, creating local structures such as islands or peninsulas that we do not find in the middle of those patches. The brown-red color, most common but mostly present on the sides, might be a background color. Guesswork: the image might map the distribution of some assortative attribute with multiple modalities (I count 7 distinct colors) over a literal or metaphorical space.

This image represents the outcome of a simulation, not empirical data. This particular simulation "illustrates how the combination of variation and selection in a model biological system can increase the average fitness of a population of mutants of a species over time" (Brockmann, 2018). As this simulation is based on a modeling of biological systems, it is not surprising that it features organic patterns. However, it is important to note that it exhibits patterns that we associate with empirical data, even though the data are not empirical (they do not consist of a *measure* of a real-world phenomenon). My next example (Figure 25) does not involve data.

Figure 25 is reminiscent of geological strata or seismographic measurements. Horizontal patches of color of various sizes are disturbed by vertical bumps that produce aligned spikes. There is a distinct rhythm to the visual patterns, only partially repetitive. However, taking a close look uncovers the deception: this is just decorative paper. The vertical alignment reveals how the image was produced: by combing patches of colored paint floating on the surface of a viscous solution, a technique known as *marbled paper*. This is not data art, despite the striking similitudes. This image is not supposed to be analyzed as a chart, yet its richness and mix of structure and irregularities prompt in my data scientist eyes a mode of sensemaking that I usually reserve for data visualization.

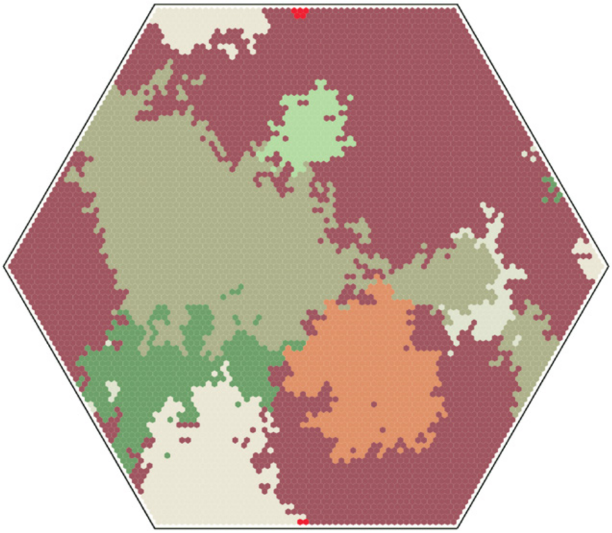


Figure 24. Screenshot from Complexity Explorables (Brockmann, 2018) "An illustration of the mechanisms involved in evolutionary processes." © Dirk Brockmann, 2020 Complexity Explorables. This work is licensed under a Creative Commons Attribution 2.0 Germany License.

Figure 25. Decorative paper from page 98 of The Great Favourite or The Duke of Lerma (1668). Original from British Library. Public domain.

My point is that the noema of big data visualization is capable of accounting for a plausible interpretation, in particular, how visual features prompt a specific angle of interpretation. My three examples do not necessarily deserve to be qualified as big data, yet they have what it takes to be instrumentalized in the rhetoric of big data because they display patterns that suggest an order to be discovered. Thus, they qualify as *big data visualizations*. The noema helps us understand why such images have a power of conviction, even in the absence of a precise interpretation. On their own, these images mean that *there is an order to this chaos*, even if this meaning is wrong.

Network maps are not *situated knowledges*, in the sense of Haraway (1988), because the mediations they involve are not visible, thereby allowing them to get too easily interpreted as if they were self-evident. This favors the form of objectivity that Haraway describes as "the god trick of seeing everything from nowhere" (1988: 581), easily leveraged by the rhetoric of big data. Not only do network mappers enact self-evidence ("Unblackboxing Gephi"*), but on their own, network maps suggest to their readers that there is an order to their chaos. I do not think that fighting against the noema of big data visualization is a winning battle, precisely because the effect is material–semiotic. The dangerous affinity of network maps with self-evidence lies in the same visual features that make them useful in a science context. Their ability to produce patterns is instrumental to mediating the network topology. I defend this view in spite of the contradictions in part of the literature on the subject. In the next chapter, I retrace the evolution of the field of graph drawing and the evaluation of layouts, and I show that it was late in accounting for the shift of network practices toward visualizing the community structure of large relational data sets.

3. THE ART OF DRAWING NETWORKS

In this chapter, I narrate the evolution of graph drawing from the 1980s to 2020. I show that networks used to be evaluated as diagrams because they were small and because the main issue was readability. During the turn to complex networks in the 2000s, node placement algorithms shifted to the role of mediating the topological structure, disregarding the aesthetic criteria of diagrams. I show that the evaluation literature was late in taking this change into account, and I propose a state of the art of network visualization techniques and their evaluation, focusing on the question of node placement. I argue that these two historical understandings of network layouts still coexist in the literature. I formalize them as distinct interpretation regimes, *diagrammatic* and *topological*, and compare their characteristics. I contend that recent layout algorithms have not been properly evaluated because the diagrammatic interpretation regime still dominates the literature, despite the two decades-old shift of practices to the topological regime.

HISTORY OF GRAPH DRAWING AND ITS EVALUATION

Here, I retrace the history of the field of graph drawing and the evaluation of graph drawings. Although network visualization is more than dot-line visualizations, I will only overview this landscape in the next subsection. For the moment, I focus on node placement algorithms and the criteria that they were designed to optimize at different points in time. Producing an image and evaluating it are two sides of the same coin and often come together. I show that the research community changed its perspective on what constitutes a good network visualization. I prioritize the papers that have paved the way toward our current understanding of the node-placement problem. For clarity, I homogenize some of the vocabulary with that used in the rest of this dissertation.

Network visualization was a practice long before anyone tried to measure the quality of a layout. Dating back to the 1930s, SNA was the first field to engage, including in the most in-depth manner, with network visualization. Moreno (1934), pioneer of this practice, called his hand-made visualizations “sociograms.” From experience, he learned how to craft them well. He notably voiced that “[t]he fewer the number of lines crossing, the better the sociogram” (pp. 95-96). This criterion would later be proven to improve readability, though not at the initiation of SNA. It is to the fields of engineering, computer science, and information design that we owe the long quest to measure the quality of graph drawing.

I must warn against a misconception about the purpose of measuring a node placement. Indeed, the main interest of quality metrics is not to assess what we already have but to produce something better. Of course, some researchers simply seek objective knowledge of existing procedures to compare the different methods of network visualization, but this endeavor is not as exigent as it might seem. Visualization is often used in an exploratory setting, and evidence is often provided by other means. Although Moreno had an idea of what makes a good sociogram, he had other ways of providing evidence. The lack of sociogram quality metrics does not jeopardize the practice of SNA, thus the field has no strong interest in assessing node placements. A quality metric is more useful to algorithm designers: engineers, mathematicians, and computer scientists. This is so because *mathematical optimization* offers an extremely broad and deep set of techniques to solve so-called "optimization problems." Not all problems are of this kind, but as all math-educated researchers know, once an issue is formalized as an optimization problem, there is a great deal of solution-seeking techniques that one can mobilize—hence the appeal to reduce an empirical problem to an optimization problem, the purpose of which is, literally, to quantify it. This is why quality metrics of all kinds are crucial to mathematicians: a quality metric is, implicitly, an optimization problem, a way of quantifying a question. Once the problem of producing "good" visualizations, whatever that may mean, is reduced to a quality metric, algorithm designers can offer ways to get an optimal result—"optimal" in the sense prescribed by the quality metric, of course. This is why algorithm designers, and not semioticians, have been proactive in the production of quality metrics. This is also why the history of node placement algorithms cannot be separated from the history of assessing the validity of network visualizations. The assessment of node layouts has been driven mainly by a need for quantification and secondarily by a desire to reflect on practices.

THE EARLY DAYS OF GRAPH DRAWING: DIAGRAMS

Moreno (1934) drew sociograms in the 1930s, with Tutte (1963) formalizing "how to draw a graph" in the 1960s; however, I chose to start with the 1980s, with answers to the practical need for drawing diagrams. Sugiyama et al. (1981: 110) started from the observation that "it is difficult to grasp the structure of a [network] readily unless [nodes] are laid out in some regular form (e.g., clustered layout) and/or unless edges are drawn in such a form that paths can be readily traced by human eyes." To produce more readable images, they proposed five complementary strategies: hierarchizing the node placement, minimizing edge crossings, straightening the lines, favoring shorter edges (bringing connected nodes closer), and balancing the edges around each node. From these premises, they proposed a strategy to draw better networks (Figure 26). For them, network visualization was also a matter of readability (e.g., straightening the lines to help follow the "paths" visually) and of mediating the topology (bringing connected nodes closer to help "grasp[ing] the structure"). They did not mention the term "aesthetics," which was soon employed to refer to such criteria.

In 1984, Peter Eades created the first force-driven placement algorithm, mimicking Newtonian physics to simulate node positions. His algorithm is the common ancestor to all force-driven layouts, including Force Atlas 2. Eades transcribed

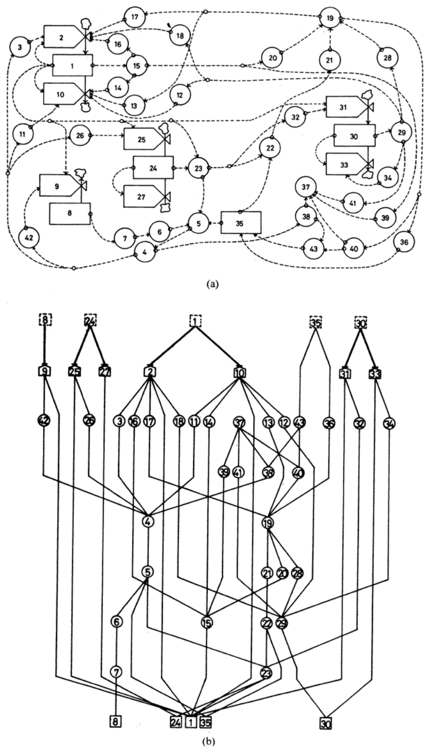


Fig. 7. (a) Diagram of the world model (Forrester [12]). (b) Hierarchical representations of the world model.

Figure 26. Figure from Sugiyama et al. (1981: Figure 7). Their strategy to optimize the readability of networks is based on hierarchies, straightening edges and minimizing crossings. They redesign the top image into the bottom one. © 1981 IEEE.

the physics of springs (for the edges) and electrical charges (repulsion between nodes). This "spring-electric model" can be seen as a proof-of-concept that was later refined. However, it has an important difference vis-à-vis its successors: it does not try to bring connected nodes as close as possible, which was one of the criteria of Sugiyama et al. (1981). Instead, it tries to have all connected nodes at a homogeneous distance. This is what a spring does: it pulls when you stretch it, but it also pushes when you compress it, trying to maintain a given length. Eades' (1984) perspective was sensibly different from those of Sugiyama et al. (1981), whom he did not cite. For him, the layout is not a matter of readability but of aesthetics. Here is how Eades (1984) framed the role of his node-placement algorithm, which he called "embedder." It "assigns locations to vertices in such a way that the resulting layout is in some sense aesthetically pleasing. The design of an embedder is a formidable task, since 'aesthetically pleasing' is a subjective concept" (p. 150). The two validity criteria used by Eades were as follows: "all the edge lengths ought to be about the same, and the layout should display as much symmetry as possible. These criteria form a part of 'aesthetically pleasing' in a wide variety of application areas. Further, we aim to produce layouts which conform to the author's somewhat subjective sense of aesthetics" (p. 150).

In the same spirit, Batini et al. (1985: 1) acknowledged that the quality of a diagram is "a hopeless matter to define formally." Thus, they conducted an empirical study to find the aesthetic criteria present in diagrams considered valid. Extending their work, Tamassia et al. (1988: 61) "investigate[d] how readability of diagrams can be achieved by means of automatic tools." Diagrams here refer to network visualizations, but the term "network" was rarely used. The authors used the term "graph drawing," hence the title of the paper: "Automatic Graph Drawing and Readability of Diagrams." Indeed, they focused on readability, understood mainly as the task of visually retracing paths in relatively small networks. They articulated their approach to interpretation around the term "aesthetics": "We use the term aesthetics to denote the criteria that concern graphic aspects of readability. A well-admitted aesthetic, valid independently from the graphic standard, is the minimization of *crossings* between edges" (p. 62). The authors reused the criteria proposed by Sugiyama et al. (1981) but changed their framing to align with Eades' (1984) perspective (his influence was acknowledged at the end of their paper). For Tamassia et al. (1988), the aesthetic criteria were legitimized by the practices observed by Batini et al. (1985). In other words, a network layout is valid when it meets a list of aesthetic criteria validated by experts following established practices.

Eades and Tamassia (1987) created and maintained a large annotated list of references that became a major landmark in discussing the problem of graph drawing. Other authors later joined the effort, and the largely updated list was published again (Di Battista et al., 1994). I mention this reference to emphasize the influence of this initial group of authors (Battini, Di Battista, Eades, and Tamassia). This list sets a standard for graph drawing, where mediating the topology is no longer a goal.

> *Readability issues are expressed by means of* aesthetics*, which can be formulated as optimization goals for the drawing algorithms. In general, the aesthetics depend on the graphic standard adopted and the particular class of graphs of interest. A fundamental and classical aesthetic is the minimization of crossings between edges. In polyline drawings it is desirable to avoid bends in edges. In grid drawings, the area of the smallest rectangle covering the drawing should be minimal. In all graphic standards, the display of symmetries is desirable. (Di Battista et al., 1994: 236)*

Sindre et al. (1993) extended these criteria and proposed a taxonomy of "pure graph aesthetics" (Figure 27). The new additions included minimizing the area occupied by the drawing, uniformizing the distribution of nodes in the drawing space, balancing the drawing over the vertical and horizontal axes, and placing the most connected nodes in the center. These criteria are no longer discussed or put in perspective. They only played the role of a product specification in designing algorithms. They now define the terms of the problem, prescribing what a readable "diagram" must look like.

AREA	minimize the area occupied by the drawing.
BALAN	balance the diagram with respect to the vertical or horizontal axis.
BENDS	minimize the number of bends along the edges.
CONVEX	maximize the number of faces drawn as convex polygons.
CROSS	minimize the number of crossings between edges.
DEGREE	place nodes with high degree in the center of the drawing.
DIM	minimize differences among nodes' dimensions.
LENGTH	minimize the global length of edges.
MAXCON	minimize length of the longest edge.
SYMM	symmetry of sons in hierarchies.
UNIDEN	uniform density of nodes in the drawing.
VERT	verticality of hierarchical structures.

Table 1: A taxonomy of pure graph aesthetics

Figure 27. Sindre et al.'s (1993) "pure graph aesthetics": criteria for interpretable network visualizations. © 1993 IEEE.

I must briefly mention the work of Kamada and Kawai (1989), who published an algorithm based on Eades and Tamassia's (1987) criteria: minimizing edge crossings and distributing nodes and edges uniformly. Their strategy sought to minimize the stress function by iteratively moving the nodes (although they did not use the term "stress"). This strategy would give birth to a distinct branch of node placement algorithms, now referred to as *stress minimization* algorithms. Although they use a slightly different strategy from force-driven layouts, these algorithms aim to solve the same problem using basically the same approach.

After Eades (1984), the next major breakthrough in force-directed networks was the algorithm of Früchterman and Reingold (1991), which quickly became popular[16] and would be implemented in most network visualization tools (e.g., Gephi and GUESS). They acknowledged Eades' (1984) perspective but distanced from it:

> *We are concerned with drawing undirected graphs according to some generally accepted aesthetic criteria [Eades and Tamassia (1987)]. … Our algorithm does not explicitly strive for these goals, but does well at distributing vertices evenly, making edge lengths uniform, and reflecting symmetry. Our goals for the implementation are speed and simplicity. … We have only two principles for graph drawing: (1) Vertices connected by an edge should be drawn near each other. (2) Vertices should not be drawn* too *close to each other. (Früchterman and Reingold, 1991: 1129)*

Früchterman and Reingold acknowledged the aesthetic criteria presented by Eades and Di Battista but preferred stating their own set of goals. As we will see, this move would become the norm.

At this point, let me highlight why it matters that Früchterman and Reingold set different goals for visualization. The criteria settled by Di Battista et al. (1994) did not aim to mediate the topology but to improve readability. This makes sense in a context of small networks, but in the 1990s, large networks, e.g., web data, were becoming available. Due to their size, they required more than readability, and the algorithm of Früchterman and Reingold delivered this yet unidentified quality. As Noack (2007a, 2007b) would argue much later, bringing connected nodes closer helped with visualizing the clusters. This goal was not part of the list of Di Battista et al. (1984), even though it was initially part of the criteria of Sugiyama

16 Their paper (Früchterman and Reingold, 1991) has 5,842 citations according to Google Scholar (13 October 2020).

et al. (1981), whose aim to make "edge lengths uniform" contradicted this goal. As it would progressively turn out, aiming for short edges was, in fact, a good way to mediate the community structure. The stress minimization approach by Kamada and Kawai (1989) initially aimed to make edge lengths uniform, leading to efficient algorithms, though at the cost of redefining its goal as specific, non-uniform edge lengths. Since the beginning, the evaluation of graph drawing has been lagging behind practice. The criteria of Di Battista et al. (1994) had already originated in a pragmatic move to define criteria following existing practices (Battini et al., 1985). Früchterman and Reingold's (1991) divergent goals emphasized the gap.

From the mid-1990s, Purchase et al. (1995) published studies explicitly aimed at assessing the validity of graph drawings, as the paper title shows: "Validating Graph Drawing Aesthetics." They focused on three commonly used aesthetic criteria and conducted an empirical experiment to assess the impact of these criteria on "the understandability of a graph drawing." The participants had to answer "three graph-theoretic questions" on a set of network visualizations, and their performance was measured. Each aesthetic criterion was measured independently with a mathematical metric. This paper was followed by "Which Aesthetic Has the Greatest Effect on Human Understanding (Purchase, 1997)?" There, Purchase expanded the criteria considered and improved her methodology. These papers were well received. Indeed, graph drawing has not been assessed empirically since Battini et al. (1985), but we must pay attention to what "the understandability of the graph" means in this work. Purchase assessed some of Di Battista and Eades' criteria (Di Battista et al., 1994; Eades, 1984; Eades and Tamassia, 1987): symmetry, minimizing edge crossings, minimizing edge bends, distributing edge angles, and fixing nodes and edges on an orthogonal grid. The participants were asked questions relating to paths, for instance, "How long is the shortest path between two given nodes?" Further, the (single) network used was very small, with just 16 nodes (Figure 28). "Understandability" here refers to following the paths. The main takeaway of this work was that minimizing edge crossings increases "understandability," a message that would be heard loud and clear in the research community. Unfortunately, this version of "understandability" was not very relevant to large networks, where paths cannot be followed. It also failed to account for the practical efficiency of Früchterman and Reingold's (1991) algorithm, now six years old, which explicitly departed from these aesthetic criteria.

The problem here is not Purchase's badly-needed endeavor. Indeed, network

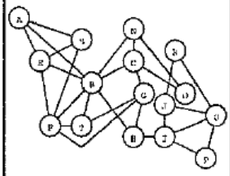
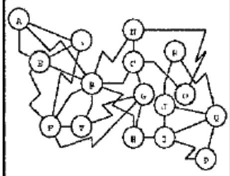
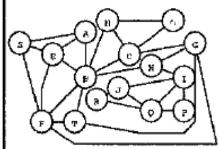
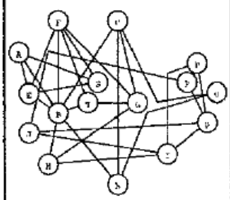
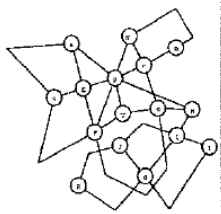
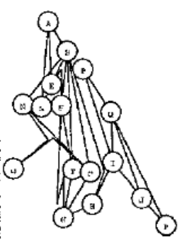
	graph	bend-less	cross-less	minangle	orthog	sym
b+		0.96	0.97	0.38	0.27	0.75
b-		0.47	0.99	0.44	0.28	0.71
c+		0.82	1	0.46	0.33	0.63
c-		0.87	0.88	0.35	0.29	0.84
m+		0.71	0.98	0.62	0.22	0.74
m-		0.82	0.98	0.16	0.26	0.79

Figure 28. Different drawings of the same network and the measure of its aesthetic criteria (Purchase, 1997). Reprinted with permission from Springer Nature Customer Service Centre GmbH: Springer Nature, Which aesthetic has the greatest effect on human understanding? Helen Purchase, © 1997.

visualization became increasingly popular, and the validity of node placements needed to be assessed in a science setting. The problem is that her work, in the continuity of Eades (1984) and Di Battista et al. (1994), *de-facto* became the reference against which to assess network layouts, despite its increasing gap with practices. Networks are no longer diagrams; they are network maps. In the mid-1990s, the state of the art of graph-drawing techniques was an algorithm known as *GEM* (Frick et al., 1995). The networks considered in this paper ranged from 16 nodes (labeled "tiny" by the authors) to 128 ("large") and more ("huge"), much more than Purchase's (1997) 16 nodes. Moreover, edge bends are no longer considered, and Frick et al. (1995) have hilariously argued that "straight-line drawings avoid bends in edges by definition" (p. 1). In fact, Frick et al. endorsed Früchterman and Reingold's (1991) alternative criteria: short edges, minimal area, and even distribution of nodes.

The gap between aesthetic criteria and practice has been addressed by different authors. Blythe et al. (1996) published a remarkable paper on the problem from the perspective of SNA. SNA has its own tradition of drawing networks, called *sociograms*, and a rich and well-established practice of network reading. Blythe et al. acknowledged the works of Batini et al. (1985) and Di Battista et al. (1994), but remarked that "almost all of this work considers aesthetics that attempt to improve graph readability from a very general point of view without considering specific applications" (p. 42). They conducted their own empirical study and, contrary to Purchase (1997), asked participants questions related to the community structure of the network. Their findings showed a clear impact of the drawing on the interpretation but also highlighted that "it is not possible to say that one drawing is the 'best' drawing of a particular social network" (p. 49). The gap between aesthetic criteria and practice was also noted by Herman et al. (2000: 26): "Actually, some aesthetics are quite arbitrary and are not seen as absolute rules any more. … Although the adjective 'aesthetic' is used, some rules were originally motivated by more practical issues." Herman et al. also addressed the need to study large networks. "In graph visualization, a major problem that needs to be addressed is the size of the graph" (p. 26).

Algorithm designers quickly adapted to the new needs of network visualization, further accentuating the gap. In 2002, Purchase updated her work with more recent layouts, including the algorithms of Frick et al. (1995; GEM), Früchterman and Reingold (1991), and Kamada and Kawai (1989). She used the same diagram-oriented aesthetic criteria from 1997 as well as networks from 5 to 30 nodes. Around the same time, two major algorithms were published. On the stress minimization branch, following Kamada and Kawai (1989), Gansner et al. (2004) proposed a more efficient strategy they labelled “stress majorization,” which showcased networks of up to 3,800 nodes. On the force-driven branch, following Fruchterman and Reingold (1991), Hachul and Jünger (2004) published an algorithm known as FM3, which produced similar results as older force-driven algorithms, though much faster. The networks showcased in the paper have up to 74,000 nodes, three orders of magnitude above those of Purchase (2002). The term “aesthetics” was no longer employed by these algorithm designers. A new generation of computer scientists was taking the lead, leaving questions of aesthetics behind. However, as we have seen, that gap actually dates back to Früchterman and Reingold (1991), who disregarded them.

THE TURN TO COMPLEX NETWORKS DURING THE 2000S

At this point, it is worth mentioning what was happening in the world of networks beyond drawing them. The 2000s was the “NS” decade. As I narrate in detail in “Epistemic Clashes in Network Science,”* the field of NS was kickstarted by a series of papers published at the end of the 1990s (Albert et al., 1999; Barabási and Albert, 1999; Watts and Strogatz, 1998). Barabási’s team made a massively impactful claim: that scale-free networks are pervasive. This claim was particularly appealing to physicists and mathematicians who postulated the existence of universal laws of nature. Indeed, it seemed that scale-free networks could be a universal signature of complexity. That claim would be disputed for the first time in 2005, leading the community to adopt the more general notions of complex networks (instead of scale-free) and heavy-tailed distribution (instead of power law). It would be disputed a second time in 2018. Providing more details would side-track us from the question of graph drawing, but these developments are presented and analyzed in detail in “Epistemic Clashes in Network Science.”* The important point is that an unprecedented number of empirical networks were analyzed in the 2000s (list in, e.g., Lima-Mendez and Van Helden, 2009), most of which were large (hundreds of nodes or orders of magnitude more) and complex. Here, the “complex” in complex networks means that a few nodes have most of the links, while most nodes have a few links (heavy-tailed degree distribution). This new material would completely change the practice of network visualization, as noted by many authors (e.g., Henry et al., 2012; Shneiderman and Dunne, 2013). First, most existing algorithms had issues with highly connected nodes, typical of complex networks, though rare in small or geometrical networks. Second, these networks changed the tasks of network analysis, and detecting the topological structure, such as core–periphery or other communities, became routine. Complex networks were too large and too intricate to allow a path-based reading. Instead, researchers needed to understand the structure of their empirical networks. As a consequence, the complex networks became the new standard against which to assess layout algorithms, replacing geometrical networks and diagrams.

Noack (2007a) made a decisive contribution with his Ph.D. thesis and a paper drawn on it (2007b), foreshadowed by his well-received but less substantial work in 2003. His research focused on measuring the quality of network "assignments," a generic concept that simultaneously covers clustering, node placement, and the ordering of matrix columns and rows. Noack defined quality measures for graph assignments, validated them, and from there found algorithms to optimize them. His stance was opposite to those of Eades, Di Battista and Purchase, mentioning "aesthetics" exactly once in his thesis as the first of his "non-goals" (2007a: 13). His approach decided visual features by optimizing an equation. His starting point was to propose a measure based on the total length of edges. This "quality metric" was normalized to eliminate known biases (drawing scale and graph density). It played the role of a theoretical standard to evaluate node placement algorithms, implicitly formalizing Füchterman and Reingold's (1991) goal of minimizing edge lengths. From there, Noack found the best "energy model" to minimize this metric, which refers to the part of a force-driven algorithm that determines the shape of the layout as opposed to the optimization part. Noack's work focused on the qualitative result, leaving aside the question of optimization. Noack called his energy model "LinLog" because it consists of a linear repulsion and a logarithmic attraction. His mathematical framework allowed him to prove that no other energy model could provide a better minimization of his quality metric. Furthermore, his energy model was "not biased towards grouping nodes with high degree, and are thus particularly appropriate for graphs with [heavy-tailed] degree distributions, which are very common in practice" (p. 454). In short, the LinLog provided the best possible minimization of edge length, aside from possible performance optimizations.

In his paper, in a subsection titled "Interpretability vs. Readability," Noack (2007b) justified how his algorithm contributed to understanding networks. For him, interpretability meant that node positions mediated the structure of the network, in contrast with readability, which simply related to an aesthetic norm.

> *The primary purpose of most energy-based graph layout techniques is to produce easily* readable *box-and-line* visualizations *of graphs. For example, the classic energy models of Eades [(1984)], Fruchterman and Reingold [(1991)], and Davidson and Harel [(1996)] primarily reward the conformance to aesthetic criteria like small and uniform edge lengths, and uniformly distributed nodes.*
>
> *Graph layout techniques may also produce* interpretable *layouts, where the positions or Euclidean distances of the nodes reflect certain properties of the graph. Examples of such properties include the density of subgraphs (in this work), the graph-theoretic distances of nodes (e.g. in [Kamada and Kawai, 1989]), or the direction of edges in directed graphs (e.g. in [Sugiyama and Misue, 1995]). Interpretable layouts can be seen as simple* models *of a graph, which reflect some properties of the graph and abstract from others, and which have the additional benefit of being easily visualizable. Visualizations of interpretable layouts can convey information about the edges without actually showing edges, which is essential for non-sparse graphs where showing all edges inevitably results in heavy clutter.*
>
> *The goal of this work are layouts that group densely connected nodes and separate sparsely connected nodes; such layouts often violate aesthetic criteria like small edge lengths or uniformly distributed nodes. (Noack, 2007b: 455)*

The epistemic reach of Noack's work has been noticed in the information visualization community, notably by Munzner (2000), who wrote her Ph.D. thesis on the interactive visualization of large networks and later published a reference book on visualization analysis and design (2014). In 2009, she proposed a model that "provides prescriptive guidance for determining appropriate evaluation approaches" to visualization. After presenting her method, she analyzed a series of visualization papers. For each, she mobilized her model to explain how authors built their validation, including Noack's (2003) LinLog paper. "Although a quick glance might lead to an assumption that this graph drawing paper has a focus on algorithms, the primary contribution is in fact at the visual encoding level" (Munzner, 2009: 925).

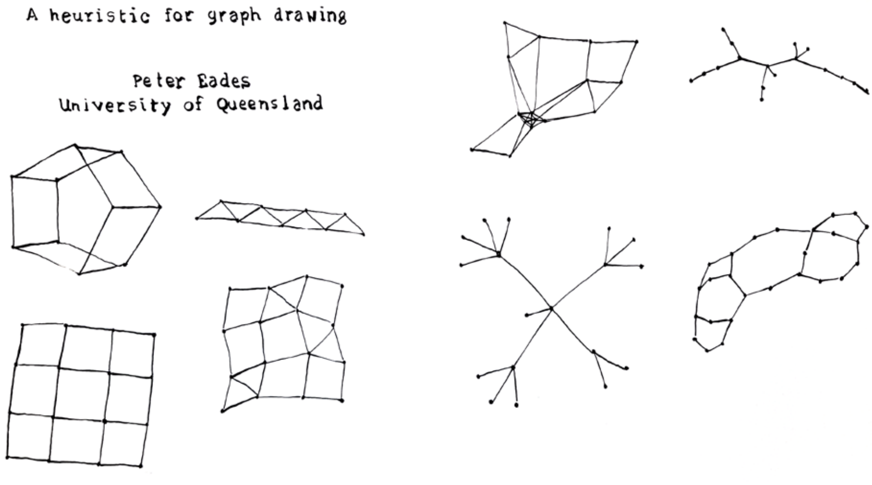
> *[The] LinLog energy model is a visual encoding design choice. Requiring that the edges between clusters are longer than those within clusters is a visual encoding using the visual channel of spatial position. One downstream validation approach in this paper is a qualitative discussion of result images, which we consider appropriate for a contribution at the encoding level. This paper also contains a validation method not listed in our model, because it is relatively rare in visualization: mathematical proof. (p. 925)*

The same year, Noack (2009) published another decisive paper drawn on his thesis, titled "Modularity Clustering is Force-directed Layout." I paraphrase his point as follows: when a force-directed layout has been used, what we see in networks are clusters, in the sense of Newman's modularity. Noack presented his work slightly differently, as a theoretical proof of unification:

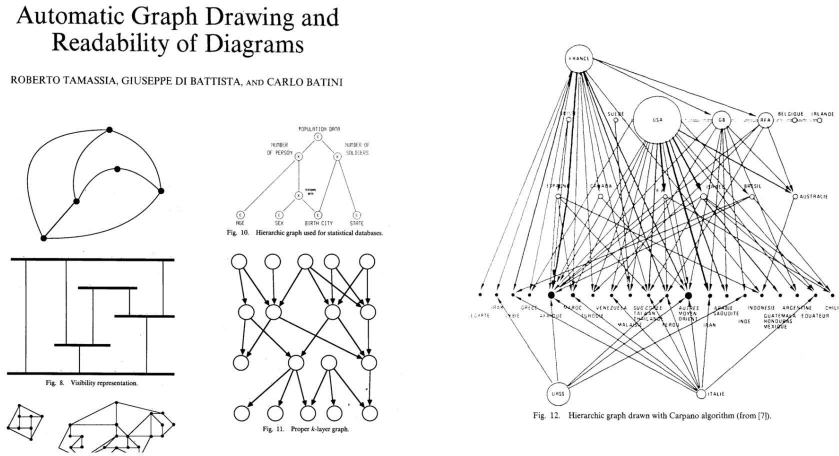
> *Requirements like the grouping of densely connected vertices are often formalized as mathematical functions called* quality measures*, and the optimization of quality measures is a common strategy for the computation of both layouts and clusterings. … This paper unifies Newman and Girvan's modularity, a popular quality measure for clusterings, with energy models of pairwise attraction and repulsion between vertices, a widely used class of quality measures for layouts. (p. 1)*

Modularity is a measure of clustering proposed by Newman (2004), which led to popular community-detection algorithms (Blondel et al., 2008; Newman and Girvan, 2004; Traag et al., 2019). If you look at Figure 5, you can see that the colors given by modularity clustering match the node positions given by a force-directed placement. The nodes of the same color are indeed grouped together. According to Noack, this is no surprise: modularity clustering and force-directed placement essentially do the same thing. Noack's work essentially put an end to the quest for the best-looking placement algorithm. Visualizing large networks remained an issue, however, with subsequent algorithms tackling the challenge of scalability (e.g., Martin et al., 2011).

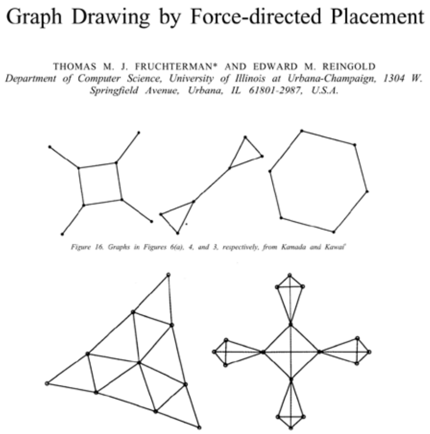
Noack's work was a turning point for network drawing and its evaluation. In Figure 29, I gather the networks pictured in major graph-drawing papers at different points in time. Three evolutions are visible. First, and most obvious, networks have become bigger. Second, diagrams have quickly disappeared: edges become dots connected by straight lines. Third, and most importantly, is the disappearance of geometric figures. Graph theory has always been interested in geometric objects (e.g., polygons, lattices). The terms "vertex" and "edge" originally referred to polygons. Such graphs were naturally used to benchmark visualization techniques, leveraging the fact that we know them. In Figure 29, you may spot trees (a, c, and f), lattices (a, c, d, and e), and Sierpiński triangles (e and f). However, from Noack's paper on, the only networks pictured are empirical data of various origins. The goal of network visualization has changed. Adamic and Glance's (2005) pioneering work on the US blogosphere was published (see also Figure 2), and it has become clear that researchers have access to large empirical networks. Like Adamic and Glance, many researchers are interested in the community structure of their networks, and Noack's approach perfectly fits that need. The LinLog is not based on the aesthetic prescription of the likes of Eades and Purchase. It aims instead to make the structure visible. Noack (2009: 6) remarked that "a layout only permits [analyzing the network's local density] if it is *consistent* with the respective clustering." Implicitly, the layout mediates topological properties into visual features. It makes the clusters visible. This could be framed as a different aesthetic perspective, motivated by the necessity to visualize large empirical networks. However, Noack dismissed this rhetoric, leaving the aesthetic consequences of his algorithm implicit. Like most algorithm designers, he did not frame the quality metric as an epistemic statement but as a quantification, a way of formulating an optimization problem: "Quality measures for

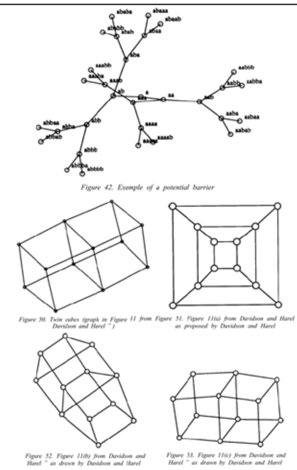


(29-a) (Eades, 1984)

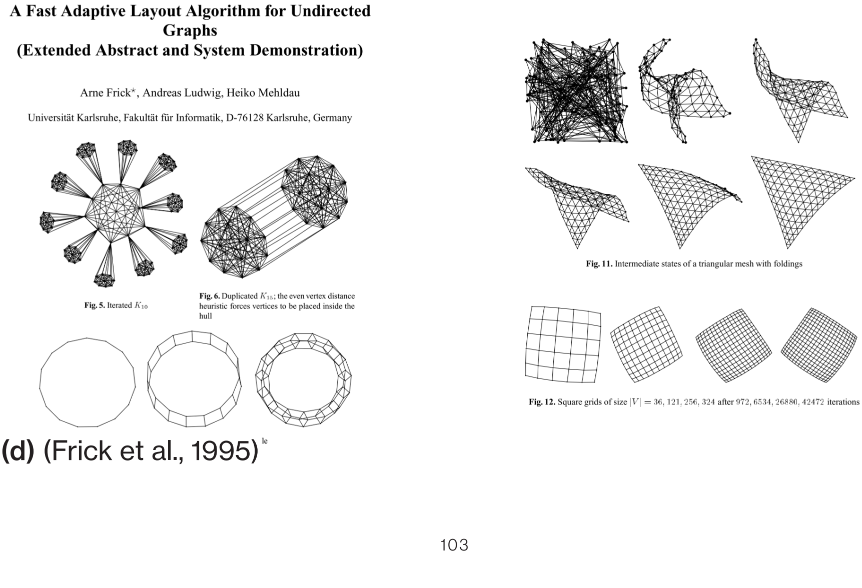


(29-b) (Tamassia et al., 1988)

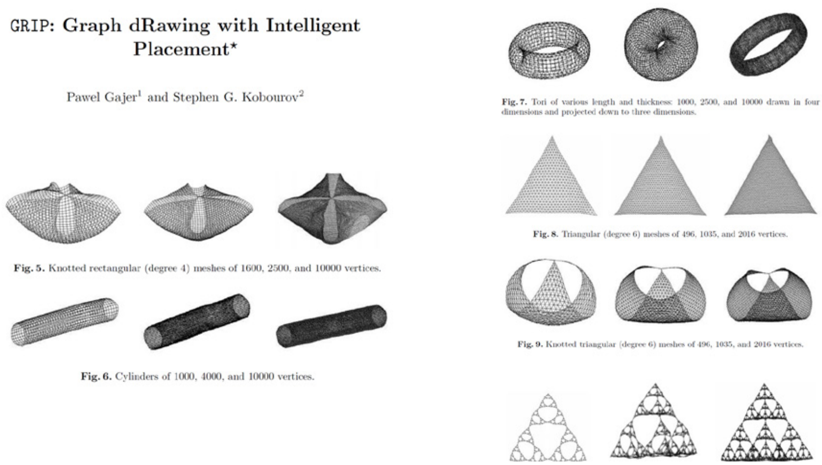




(c) (Früchterman and Reingold, 1991)



(d) (Frick et al., 1995)


GRIP: Graph dRawing with Intelligent Placement*

Pawel Gajer[1] and Stephen G. Kobourov[2]

Fig. 5. Knotted rectangular (degree 4) meshes of 1600, 2500, and 10000 vertices.

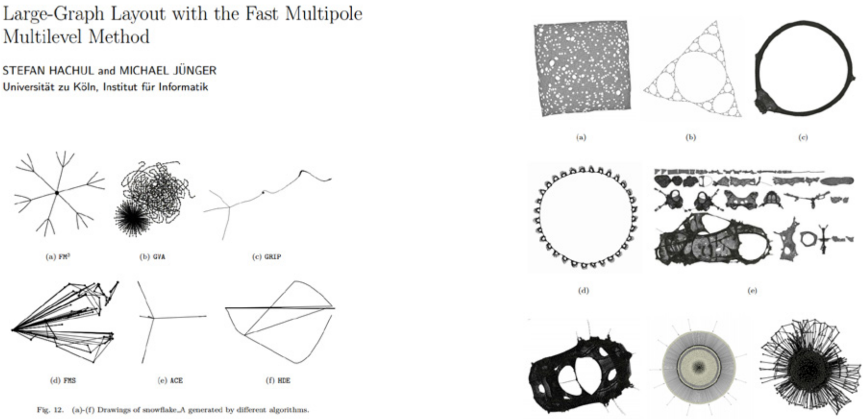
Fig. 6. Cylinders of 1000, 4000, and 10000 vertices.

Fig. 7. Tori of various length and thickness: 1000, 2500, and 10000 drawn in four dimensions and projected down to three dimensions.

Fig. 8. Triangular (degree 6) meshes of 496, 1035, and 2016 vertices.

Fig. 9. Knotted triangular (degree 6) meshes of 496, 1035, and 2016 vertices.

(29-e) (Gajer and Kabourov, 2001)


Large-Graph Layout with the Fast Multipole Multilevel Method

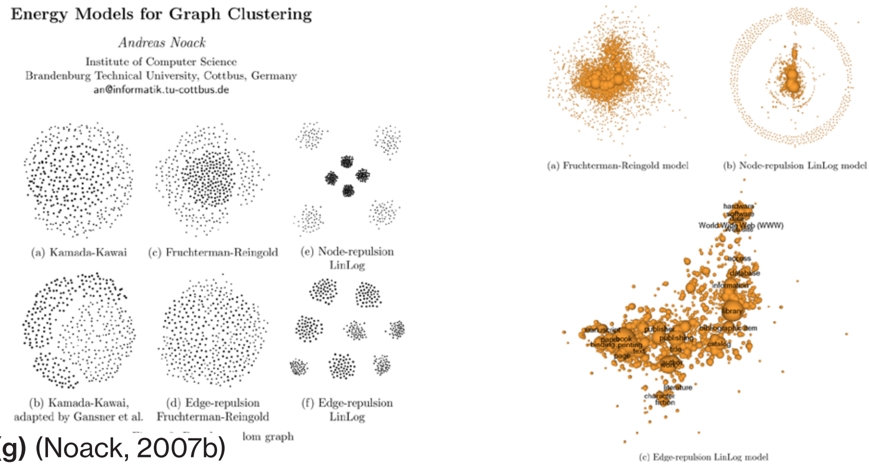
STEFAN HACHUL and MICHAEL JÜNGER
Universität zu Köln, Institut für Informatik

(a) FM³ (b) GVA (c) GRIP
(d) FMS (e) ACE (f) HDE

Fig. 12. (a)-(f) Drawings of snowflake_A generated by different algorithms.

(a) (b) (c) (d) (e) (f) (g) (h)

(f) (Hachul and Jünger, 2005)


Energy Models for Graph Clustering

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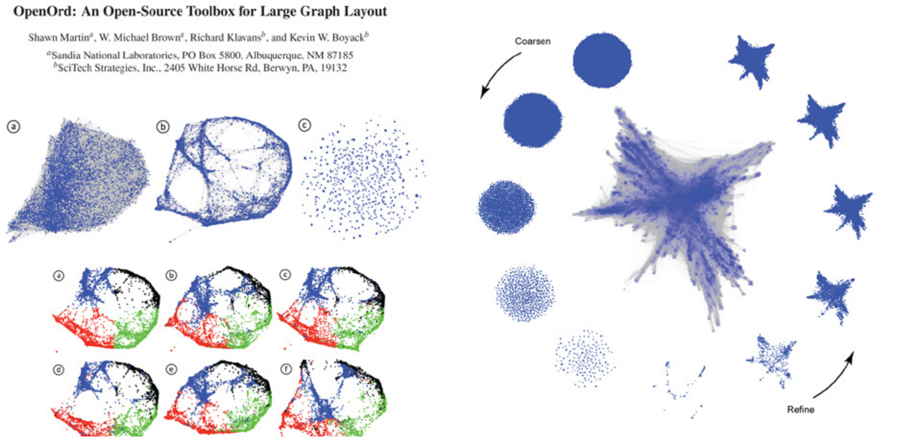
(a) Kamada-Kawai (c) Fruchterman-Reingold (e) Node-repulsion LinLog
(b) Kamada-Kawai, adapted by Gansner et al. (d) Edge-repulsion Fruchterman-Reingold (f) Edge-repulsion LinLog

lom graph

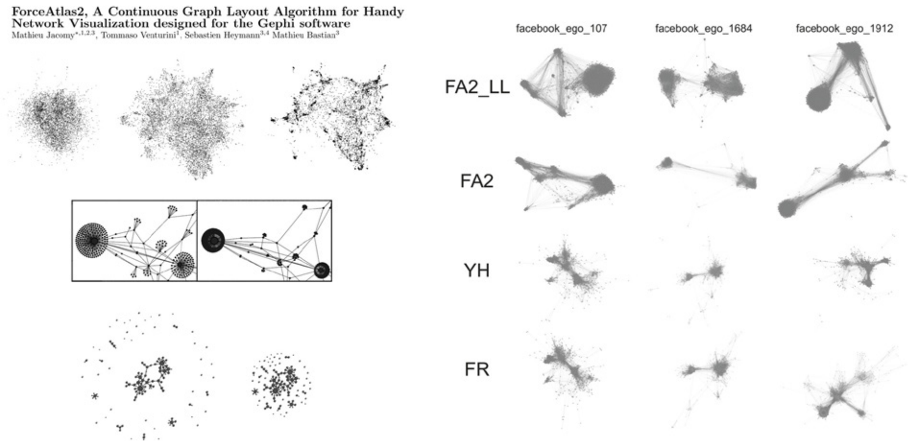
(a) Fruchterman-Reingold model (b) Node-repulsion LinLog model

(c) Edge-repulsion LinLog model

(g) (Noack, 2007b)



(h) (Martin et al., 2011)



(i) (Jacomy et al., 2014)

Figure 29. Pictures from graph-drawing publications over the years. Diagrams with boxes and bended edges were replaced by dot-line pictures, networks got bigger and bigger, and geometrical networks were replaced by empirical networks. Noack (2005) is the turning point. (a) Drawn after Eades (1984); (b) Tamassia et al. (1988). © 1988 IEEE.; (c) Früchterman and Reingold (1991). © 1991 John Wiley & Sons, Ltd; (d) Frick et al. (1995). Reprinted with permission from Springer Nature Customer Service Centre GmbH: Springer Nature, A fast adaptive layout algorithm for undirected graphs (extended abstract and system demonstration), Arne Frick, Andreas Ludwig, Heiko Mehldau, © 1995; (e) Gajer and Kabourov (2001). Reprinted with permission from Springer Nature Customer Service Centre GmbH: Springer Nature, Graph drawing with intelligent placement, Pawel Gajer and Stephen G. Kobourov, © 2001; (f) Hachul and Jünger (2005). Reprinted with permission from Springer Nature Customer Service Centre GmbH: Springer Nature, Drawing large graphs with a potential-field-based multilevel algorithm, Stefan Hachul, Michael Jünger, © 2005; (g) Noack (2007b). Reproduced with permission.; (h) Martin et al. (2011). Reproduced with permission.; (i) Jacomy et al. (2014).

representations of networks formalize what is considered as a *good* representation, and allow to compute good representations automatically using optimization algorithms" (2009: 1). Implicitly, his text states that a "*good*" layout is one with an optimal "separation of communities."

BEYOND READABILITY: MEDIATING NETWORK STRUCTURE

A word on my own force-driven layout algorithm, Force Atlas 2. I started developing it in 2006, knowing nothing of Noack's work and relying solely on Früchterman and Reingold's (1991) energy model. My goal was to understand how such algorithms worked by monitoring them. Indeed, I was initially using the tool GUESS (Adar, 2006), where the steps of the simulation were concealed behind a loading bar. My first move was to open the black box and display how nodes move from step to step. This experiment would become "Gephi"* (Figure 3). For practical reasons, I tinkered with the energy model to obtain more satisfying results. As Gephi developed, my algorithm naturally became part of it, under the name "Force Atlas". In my tinkering, I had unknowingly reached a similar energy model to Noack's, though via a different path. I had no grand rationale and no idea what it corresponded to. I only knew that it worked well in practice. In 2009, Diminescu's research group, where we developed Gephi to help scholars study the web of migrants, organized a seminar on network visualization. We invited the most prominent French researcher on information visualization to give a keynote in the hope of discussing our work with him. He gave his keynote but got angry after our work. He told us that we were wasting research money reinventing solutions to already solved problems. He told us that the best algorithm had already been found, which is how I learned about Noack's work. We subsequently incorporated Noack's energy model as an option in Force Atlas. As we make clear in our paper "Force Atlas 2,"* published much later (2014), our layout algorithm consists of an assemblage of algorithmic techniques from other authors (following Rieder, 2020: 93, "[a]lgorithmic techniques can be seen as technical elements that are combined into technical individuals, that is, into working systems"). Our only innovations were a banal energy model (halfway between Früchterman-Reingold and the LinLog) and a way of optimizing the convergence of the simulation. Nevertheless, regardless of the novelty of the paper, Force Atlas 2 made the practical contribution of integrating a number of pre-existing algorithmic techniques, including Noack's energy model, into a coherent whole. It is a feat of engineers rather than computer scientists, and I do not mean this in a bad way. I am well aware that many researchers would rather have a better apparatus than a new batch of papers to read. This is precisely why it is worth noting that the “Force Atlas 2”* paper is well cited because it documents a piece of the popular Gephi and not because it produces a better placement than its predecessors.

I argued above that Noack’s LinLog marked a turning point in network layout aesthetic criteria. However, as we have seen, part of the evaluation of network visualizations has been lagging behind practice. Tasks dedicated to identifying topological patterns, such as clusters, gradually appeared in the literature. Early on, McGrath et al. (1997: 236) showed, in an experimental study of small networks visualized by different layouts, that the “spatial arrangement has a significant impact on viewers’ judgments of prominence, bridging and grouping.” For a long time, however, the main criteria remained Purchase’s (1997) path-following tasks and the minimization of edge crossings. When Lee et al. (2006) proposed a taxonomy of network-reading tasks, they featured the task to “find the shortest path between two nodes” as well as the task to “identify clusters.”

One year later, Bennett et al. (2007) surveyed the different aesthetic criteria for graph drawing, mostly following the perspective represented by Purchase (2002). They noted that the criterion “[b]y far the most agreed-upon … is to *minimize the number of edge crossings*” (p. 3). The minimization of edge length, which drove all force-driven layouts since Früchterman and Reingold (1991), played an anecdotal role in their review.

Van Ham and Rogowitz (2008: 1333), on the contrary, acknowledged the “meteoric growth in the availability of [large and complex networks]” and considered on an equal footing “layout metrics” such as “edge crossings” and “cluster metrics” such as “cluster separability.” However, although Noack’s LinLog was mentioned, the authors did not acknowledge the connection between minimizing edge lengths and displaying clusters.

Dunne and Shneiderman (2009: 1) proposed raising user awareness of “the importance of [readability metrics] for their graph drawings and providing users with computer-assisted layout manipulation tools.” They formalized the readability metrics offered in their own network analysis instrument, SocialAction. The metrics discussed were essentially from Purchase’s (1997) seminal [readability metrics] comparison, but they nevertheless added “spatial layout & grouping” and “edge length” (p. 2).

Von Landesberger et al. (2011: 2) proposed a state-of-the-art of the visual analysis of large graphs considering "in a unified way the aspects of *visual representation*, *user interaction*, and *algorithmic analysis*." They acknowledged the goal of mediating the structure of the network, stating that Früchterman and Reingold's algorithm achieves "a good space density" and that Noack's LinLog achieves "a good clustering of nodes" (p. 7). Aesthetics were mentioned but not emphasized: "The main challenge is the layout (i.e., the placement of the nodes) so that graph readability and certain notions of graph aesthetics are supported … Typical requirements include that the nodes do not overlap, the number of edge crossings is minimized, edge length is homogeneous, and in general, graph substructures are easily recognizable" (p. 7).

One year later, Gibson et al. (2012) proposed their own survey of graph-drawing techniques. They acknowledged Purchase's contribution but also commented on

> *the type of tasks she asked her users to complete. These were finding shortest paths, identifying nodes to remove in order to disconnect the graph and identifying edges to remove in order to disconnect the graph. A particular consideration is whether these tasks are representative of those carried out by users in visual network analysis. … Noack's [(2007b)] LinLog layout is optimised for clustering to give a clear representation of the structure in the network and van Ham and Rogowitz [(2008)] found users tried to optimise clustering ahead of any other aesthetic metric also indicating users are more concerned with overall structure. Another aim for layout should then be to support users in tasks concerned with overview, structure, exploration, patterns and outliers [(Lee et al., 2006)]. (p. 27)*

Finally, Eades' (2014) "in transition to retirement," in his keynote to the Symposium on Visual Languages and Human-Centric Computing, revisited the old paper by Batini et al. (1985) where this all started, *What is a good diagram?* He mentioned the "hopeless" task of formalizing a quality metric for network layouts, paying tribute to Batini et al., of course, as well as Sugiyama et al. (1981), and Purchase. He proceeded to "review the history of quality metrics for graph visualization" but also to "suggest a new approach. The new approach is motivated by two observations: (1) the size of data sets is much larger now than ever before, and it is not clear that established quality metrics are still relevant, and (2) there is a disparity between methods used in practice and methods used in academic research" (p. 1). Eades acknowledged the existence of two distinct ways of validating "graph visualization": "readability" and "faithfulness," the latter corresponding to the mediation of the topological structure. "Readability metrics measure how well the human user perceives the diagram; these metrics have been extensively investigated and they are (at least partially) understood. Faithfulness metrics … measure how well the diagram represents the data; these metrics are not well developed and they are poorly understood" (p. 1). After thirty years, the father of network visualization acknowledged the gap between graph-drawing practice and evaluation and endorsed the approach that algorithm designers have long adopted, placing the nodes so that their distances say something about the topological structure. In 2019, he co-authored a paper measuring "how well different graph drawing algorithms visualize cluster structures in various graphs; the results confirm that some algorithms which have been specifically designed to show cluster structures perform better than other algorithms" (Meidiana et al., 2019).

From the mid-2010s, the research community on graph drawing made the distinction between readability and "faithfulness," although "faithfulness" was not always the preferred term. Dunne et al. (2015) recently endeavored to "quantify known readability issues," but they almost entirely omitted the question of faithfulness, using a rhetoric that equates "to extract meaning" with being "readable." Nguyen, Eades, and Hong (2016) developed the research mentioned in Eades' (2014) keynote, underscoring the distinction between "readability criteria" and "faithfulness criteria." While "readability" referred to the same criteria as, for instance, those of Dunne et al. (2015), "faithfulness" referred to "fidelity" and "reconstructability," in the opposite meaning of Tufte's (1983) "lie factor." "Intuitively, a graph drawing algorithm is 'faithful' if it maps different graphs to distinct drawings" (Nguyen, Eades, and Hong, 2013: 566). They maintained that "[a] good graph visualization method should achieve both faithfulness and readability; in practice, however, there may be a trade-off between the two ideals" (Nguyen, Eades, and Hong, 2016: 7).

When Vehlow et al. (2015) proposed a state of the art of the visualization of group structures in graphs, they accounted for Noack's (2009) point that force-driven layouts display groups. "By placing related or similar vertices next to each other, group structures can be already indicated implicitly" (p. 25). Citing them, Kobourov et al. (2015) convoked the Gestalt law of proximity to explain why we see groups in such layouts:

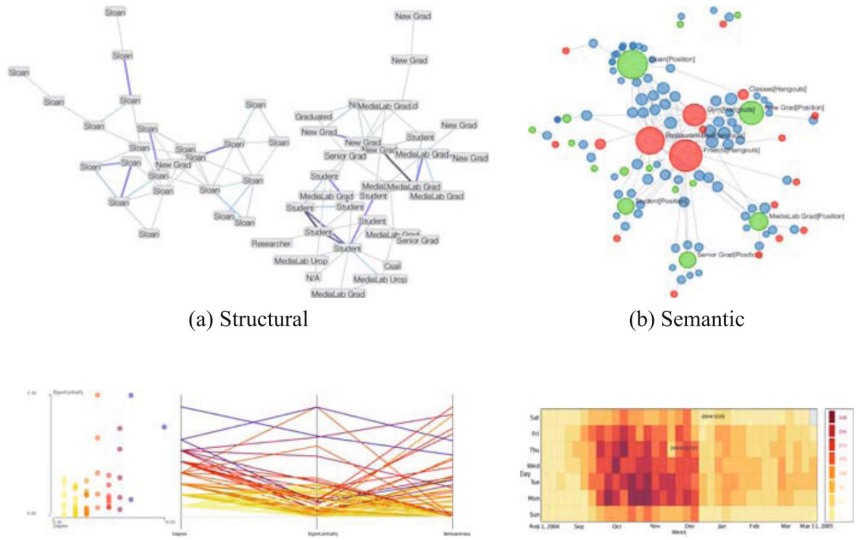
> *The principle of proximity suggests that elements close to each other are perceived as a group. In a node-link diagram this results in nodes which are close to each other being perceived as groups forming clusters. Most of the algorithms to visualize clustered graphs in the form of a node-link diagram rely on this intuition. The principle of proximity is also used by force-directed algorithms, which require that adjacent nodes are close (attractive forces), and that non-adjacent nodes are far apart (repulsive forces). (p. 559)*

Soni et al. (2018) proposed an experimental study of participants' ability to perceive graph properties for a given graph layout. These properties are not the community structure argued by Noack; rather, they are the graph density and average local clustering coefficient. However, the approach was clearly topological (see also Kypridemou et al., 2020). Meidiana et al. (2019: 1) also defended their interest in mediating the network's topology:

> *The quality of a drawing of a graph is often measured using aesthetic criteria which rate the readability of the visualization, such as the number of edge crossings or symmetry. However, these measures become less significant when working with large graphs. More recent work considers quality metrics more extensible to large graphs, such as shape-based metrics which compare the original topology of a graph to one derived from the positioning of vertices in its drawing.*

NETWORK VISUALIZATION: STATE OF THE ART

Dot-line diagrams may be the most popular representation of networks, but they are not the only one. In fact, matrices are also very common; however, as they are not specific to networks, they are rarely used to represent networks in popular culture. An untrained reader cannot easily see the network in the matrix. Diagrams are a familiar form of networks, and we have just seen that drawing them has a rich tradition in science and engineering. Moreover, networks can also be visualized with strategies that are not specific to networks, for instance, plotting the nodes on a circle or on two axes, like in a scatter plot. Herman et al. (2000) proposed a survey of these techniques, and Correa and Ma (2011) proposed a taxonomy of (social) network visualizations (Figure 30). Their first type, the most common, consisted of *structural* visualizations and included dot-line network maps, matrices, and hybrid visualizations mixing the two (e.g., Nodetrix, see Henry and Fekete, 2007). They focused on displaying the link structure



(a) Structural (b) Semantic

(c) Statistical (d) Temporal

Figure 30. Correa and Ma's (2011) typology of social network visualizations.

of the network. Conversely, the *semantic* type emphasizes the meaning of the entities and relationships over their structure. *Temporal* visualizations are dedicated to data that are both relational and temporal, and the *statistical* type visualizes nodes and edges with strategies that are not specific to networks (e.g., bar charts).

Even within the dot-line family, not all visualizations use force-directed node placement algorithms. Many strategies exist, with the aim of solving different kinds of issues. Let me acknowledge them before I focus on force-directed layouts. Gibson et al. (2012) provided an excellent overview of the different techniques, including a detailed focus on the variation within the force-directed family (see also Von Landesberger et al., 2011). I have mentioned the stress-minimization technique, a cousin of force-directed placement. Gansner et al. (2004) proposed an efficient variation that they called "stress majorization," which is based on a simple idea: a stress function expresses how different the layout is from an ideal set of distances. We try to find a solution that we know might not be optimal, but which is guaranteed to be satisfying and converges without much trouble. Some strategies combine that kind of layout with other techniques, for instance, the group-in-a-box approach (Rodrigues et al., 2011) popularized by NodeXL (Figure 31). Other strategies are entirely different, such as the Hive plot approach (Krzywinski et al., 2012), which arranges nodes radially, depending on their attributes (Figure 32).

Networks also come in different types, and each type has dedicated visualization techniques. The fact is that links can be oriented or not, weighted or not, or the presence of time-dependent attributes can naturally call for different visualization strategies. For instance, Mc Gee et al. (2019) offered state-of-the-art multi-layer networks, also called heterogeneous or multimodal, where different kinds of links coexist. Each type of link can be conceptualized as a layer, and visualizing these layers becomes an issue, for instance, when we need to compare them.

Brandes and Wagner (2004) proposed a tool to analyze social networks (Visone) and stated what visualization entails from their standpoint. “Visualized information must neither be misleading nor hard to read. Hence there are two obvious criteria for the quality of social network visualizations (1) Is the information manifest in the network represented accurately? (2) Is this information conveyed efficiently?” (p. 5) They also proposed a complete method to analyze networks.

> *The purpose of social network analysis is to identify important actors, crucial links, subgroups, roles, network characteristics, and so on, to answer substantive questions about structures. There are three main levels of interest: the element, group, and network level. On the element level, one is interested in properties (both absolute and relative) of single actors, links, or incidences. … On the group level, one is interested in classifying the elements of a network and properties of subnetworks. … Finally, on the network level, one is interested in properties of the overall network such as connectivity or balance. (p. 3)*

Hu and Shi (2015) reviewed different node placement techniques for visualizing large graphs. They reviewed force-driven placement algorithms and related techniques. Some techniques perform optimizations and can be used together to a certain extent, for instance, graph coarsening (“topology compression”) and fast-force approximation (what we call “Barnes Hut” in “Force Atlas 2”*). They also reviewed stress majorization techniques and what they called the “strain model,” usually known as multidimensional scaling (MDS). MDS is a classic statistical technique that is also used in non-network situations where distances are involved. “Stress” and “strain” techniques both aim to produce embedding whereby the distances between edges are as close as possible to an ideal. They also reviewed the high-dimensional embedding algorithm (HDE), which performs a different kind of dimensionality reduction to that performed by MDS,

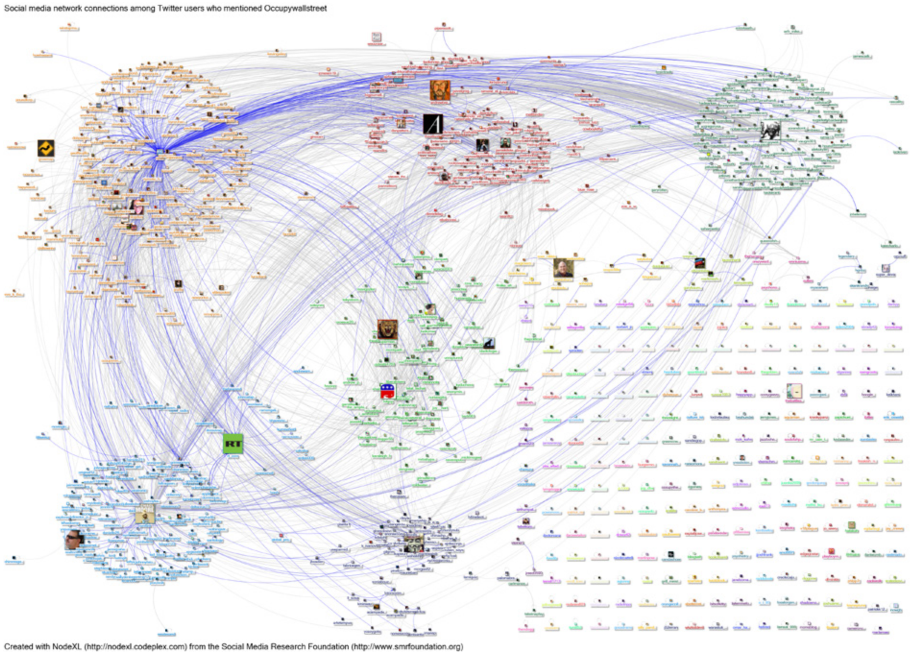


Figure 31. Social media network connections among Twitter users who mentioned Occupy Wallstreet. Created with NodeXL by Marc Smith. Licensed under CC-BY-2.0.

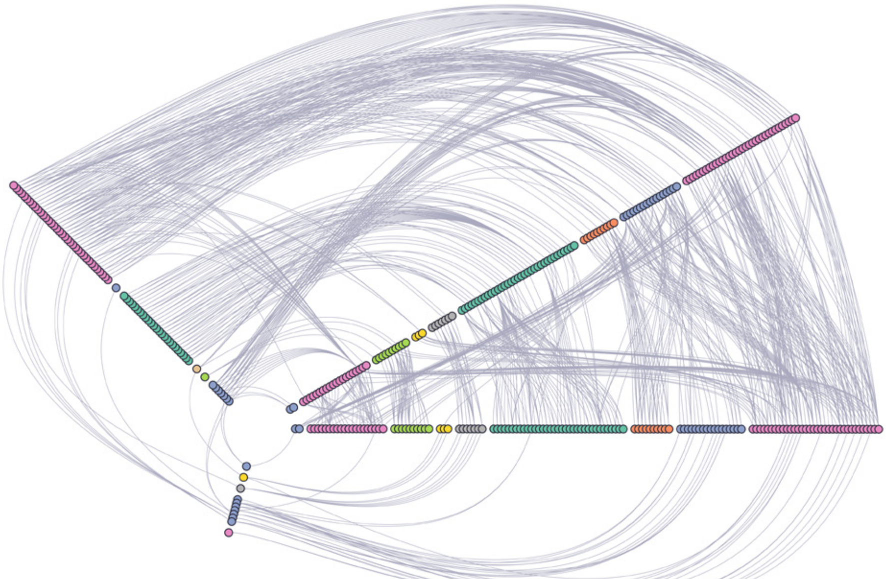


Figure 32. Code dependencies in the library Flare rendered as a hive plot.

and spectral algorithms, which leverage properties of adjacency matrices to try to minimize the distances between node pairs. They concluded that even the most promising techniques have a hard time dealing with real-word data. "Although lossless compression of large graphs can be critical to understand the details of the original graph, it is extremely difficult to achieve on real graphs with small world nature" (p. 126).

For Correa and Ma (2011),

> *[t]he purpose of a visualization is to allow users to gain insight on the complexity of social dynamics. … Numerous layout algorithms have been proposed, each of them with its strengths and weaknesses. In general, we can highlight a number of high level properties that a layout must satisfy: (1) The positioning of nodes and links in a diagram should facilitate the readability of the network. (2) The positioning of nodes should help uncover any inherent clusterability of the network, i.e., if a certain group of nodes is considered to be a cluster, the user should be able to extract that information from the layout, and (3), the position of nodes should result in a trustworthy representation of the social network, or, in layman terms, the visualization should not lie. (p. 310)*

Brandes and Pich (2009) proposed an experimental study of inter-node distances for different node placement techniques: force-driven, multidimensional scaling, and stress majorization. They concluded that "if the goal is to represent the distances in a graph well, a combination of two simple algorithms based on variants of multidimensional scaling is to be preferred because of their efficiency, reliability, and even simplicity" (p. 218). They also noted that "[t]he distance-based approach yields poor results on certain classes of graphs, which include small worlds and other graphs with many shortcuts or low diameter, and scale-free graphs with highly skewed degree distributions, large 1-shells, or other forms of structural imbalance" (p. 228). Unfortunately, these kinds of networks are the most common in the social sciences and humanities. Thus, their findings do not directly help scholars use networks in practice. It is, nevertheless, useful to look at how they framed the goal of network visualization. They used three criteria: quality, scalability, and simplicity. The latter two refer to the algorithm more than the layout, assessing whether "the algorithm scales to very large graphs" and "is easy to understand and implement" (p. 218). The first one, quality, spells out a validity criterion for layouts: that "pairwise distances between [nodes] are represented well." The formulation may seem imprecise, but the authors referred to the fact that multidimensional scaling techniques, including stress minimization, are explicitly designed to approach given distances. Conversely, they considered that "the quality criterion is implicit on force-directed algorithms" (p. 218). They considered a layout better (more valid) when given distances are well respected in the resulting dot-line diagram. However, as we have seen, complex networks perform poorly in that regard.

The recent paper by Soni et al. (2018) on how we perceive the properties of networks through visualization proposed a new framing of the question. The authors started their abstract as such: "When looking at drawings of graphs, questions about graph density, community structures, local clustering and other graph properties may be of critical importance for analysis. While graph layout algorithms have focused on minimizing edge crossing, symmetry, and other such layout properties, there is not much known about how these algorithms relate to a user's ability to perceive graph properties for a given graph layout" (p. 1). The paper is an empirical study of different visualizations techniques and tests whether one can estimate certain properties of the network. It states that a validity criterion is being able to visually retrieve certain properties of the network. As we have seen, the literature on graph layout evaluation is slowly shifting to the question of mediating the topology. In the next section, I offer a formalization of this shifting.

DIAGRAMMATIC VS. TOPOLOGICAL INTERPRETATION REGIMES

I formalize here two interpretation regimes that coexist in the current literature on network visualization. The *diagrammatic regime* was inherited from the early need to make diagrams readable, while the *topological regime* emerged during the turn to complex networks, when node placement algorithms focused on mediating the topology. In the first section of this chapter, I have unfolded the dynamic of these regimes in the academic literature over the last 40 years. I will now put aside the question of time and compare them directly, as summarized in Table 1. This expands an argument that Venturini, Jensen, and I offer in "What Do We See When We Look at Networks?"* It leverages the idea that ambiguity is not always something we need to get rid of because, sometimes, it is simply a feature of the data. This idea separates the two different regimes of interpretation of network visualizations we encountered in the literature, which we called "diagrammatic" and "topological." I do not develop here the argument on ambiguity, but I will return to it in the next chapter. In addition to this argument, our paper presents a case study of a network on Jazz music, which I do not reproduce here.

The *diagrammatic* interpretation regime is based on the premise that seeing the signs is understanding the signs. It is appropriate for small networks (100 nodes or less) and was inspired by the need to build readable diagrams (hence the name). In this regime, a good visualization separates the signs, so that we can identify them individually, and organizes them so that we can navigate the image in good conditions. The signs are nodes (dots) and edges (lines) but also, when relevant, boxes, arrows, labels, and so on. Importantly for us, the node placement only serves this form of legibility. Node distances have no direct meaning. A visualization is evaluated by aesthetic criteria such as "minimizing edge crossings" or "reflecting inherent symmetry" (Früchterman and Reingold, 1991; Purchase et al., 1997; Purchase, 2002).

After the turn to complex networks in the mid-2000s, the availability of large empirical networks created a new need. The strategies that were successful in the diagrammatic interpretation regime could not adapt to these new cases. There were so many nodes and edges that we could no longer ensure the readability of each individual element. The presence of hubs, i.e., highly connected nodes, rendered older algorithms inefficient. New interpretation regimes emerged from practice. Indeed, older algorithms (e.g., Eades, 1984) had the property to visually manifest some topological structures through node placement. This property was secondary, but in this new regime, it became the main way to make networks readable. New algorithms (e.g., Noack 2007b) were developed specifically to visualize the community structure as density patterns (visual clusters). As interpretation now mainly relied on mediating the topological structure of the network through node placement, we called it *topological*.

The two regimes coexist in today's literature. I demarcated them to highlight their different origins and criteria, but nothing prevents you from interpreting a large complex network diagrammatically or a small network topologically. You might have reasons for doing so. I contend, however, that evaluating recent force-driven algorithms from a diagrammatic perspective misses their point and misrepresents practice. In the wake of Noack (2007a), algorithm designers have tended to adopt the topological perspective. However, in the information design

Interpretation regime:	*Diagrammatic regime*	*Topological regime*
Typical type of data visualized	Diagram	Complex network
Typical size range	10 to 100 nodes	100 to 1M nodes or more
Networks used as examples in algorithm papers	Empirical diagrams, polygons, trees, lattices, 3D meshes, Sierpiński triangles	Empirical complex networks, 3D meshes, lattices
Evaluation criteria	Aesthetic criteria: Minimizing edge crossings, Minimizing edge bends, Homogeneous edge lengths, Alignment...	Representing the community structure
Interpretive tasks	Identifying nodes, edges and local structures, following paths.	Evaluating density-based topological properties: community structure, core-periphery relations.
Representation in the academic literature **before** the complex network turn (~2005)	The only regime represented	Not represented
Representation in the academic literature **after** the complex network turn (~2005)	Secondary regime	Dominant regime
Ambiguity	A readability problem to eliminate	A date property to represent

Table 1: The two main interpretation regimes of network visualizations

community, "readability metrics" are still in use to evaluate network visualizations (e.g., Dunne and Shneiderman, 2009; Shneiderman and Dunne, 2012). There is some degree of confusion on how network maps mediate the topology. I have found a good example in Munzner's (2014) reference book on visualization and its evaluation. She acknowledges the function of topology mediation, but she (mainly) illustrates it with the aesthetic criteria of the diagrammatic regime.

> *Node-link diagrams in general are well suited for tasks that involve understanding the network topology: the direct and indirect connections between nodes in terms of the number of hops between them through the set of links. Examples of topology tasks include finding all possible paths from one node to another, finding all possible paths from one node to another, finding the shortest path between two nodes, finding all the adjacent nodes one hop away from a target node, and finding nodes that act as a bridge between two components of the network that would otherwise be disconnected. (Munzner, 2014: 203-204).*

Of course, for historical reasons, the evaluation of network visualizations from the topological standpoint (see, e.g., Kypridemou et al., 2020; Soni et al., 2018) is much less developed in the literature than from the diagrammatic standpoint. It maintains the misunderstanding that the role of layout algorithms is to make the nodes and edges readable. I also hypothesize that the topological interpretation regime is more difficult to quantify, for instance, because it requires a model of visual cognition. In "Translating Networks,"* Grandjean and I proposed an overview of the correspondence between topology and visual features. In the next chapter, I embrace the topological perspective and discuss more closely how force-driven layouts mediate the structure of networks.

4. WHAT DO WE SEE WHEN WE LOOK AT NETWORKS?

THE SEMIOTIC PROBLEM IS THE LAYOUT

The complicated history of graph-drawing quality metrics shows that readability is not the only relevant concern, which is, perhaps, not surprising. A diagram is not such a special visualization, after all. It does not bear a close resemblance to a map, and its semiotics can be properly analyzed by the classic tools of information visualization, e.g., visual variables (Bertin, 1967), channels (Munzner, 2014), data density, and lie factor (Tufte, 1983), etc. Munzner (2014) articulated these different elements into a coherent approach to evaluating data visualizations, including networks. Diagrams and small networks fit well in this framework. Like all other types of visualizations, they raise readability issues that can be addressed. The real problems arise with large networks, where the reading depends mostly or solely on node positions.

> *Analyzing the visual encoding created by force-directed placement is somewhat subtle. Spatial position does not directly encode any attributes of either nodes or links; the placement algorithm uses it indirectly. A tightly interconnected group of nodes with many links between them will often tend to form a visual clump, so spatial proximity does indicate grouping through a strong perceptual clue. However, some visual clumps may simply be artifacts: nodes that have been pushed near each other because they were repelled from elsewhere, not because they are closely connected in the network. Thus, proximity is sometimes meaningful but sometimes arbitrary; this ambiguity can mislead the user. (Munzner, 2014: 204)*

As argued in Chapter 2, dot-line visualizations of large networks are different because they involve many signs. This proliferation of signs, characteristic of big data visualizations, has changed the way we make sense of these signs. Interpretation is no more about reading each sign than it is about exploring the relations between them and finding patterns. Furthermore, this sensemaking process cannot be appropriately analyzed with the notion of readability. At least in the literature about graph drawings, readability assumes that seeing is understanding. To put it simply, interpreting a diagram is mainly about accessing the signs: nodes, edges, and labels. For this reason, early quality metrics were often about what *not* to do: avoid overlappings, avoid edge crossings, avoid edge bends. This is also why aesthetic criteria are normative about visual structures: align, use symmetries, distribute signs across space. The same way that text readability tells nothing about the literature, network readability tells nothing about how we interpret patterns. Since the 2000s, the research community seems to have generally agreed that understanding networks is not only about readability but also about interpreting patterns.

Let me clarify a possible misunderstanding. Even though I highlighted the limits of the notion of readability, one should not underestimate the ability of semiotics and information design to analyze big data visualizations, especially large network maps. Gestalt theory, specifically, has been effective at analyzing our perception of many objects and has been applied to network visualization (Bennett et al., 2007; Kobourov et al., 2015; Van Ham and Rogowitz, 2008). Semiotics are equipped to describe how we perceive patterns and can help us discuss how we interpret networks. The problem is elsewhere. In a nutshell, pattern reading is difficult to quantify. Readability is relatively easy to quantify because it only cares about accessing the signs, regardless of their meaning. Symmetry, edge crossings, and alignment can all be formalized into equations; however, the ability to manifest topological properties visually depends on said properties. It is difficult to build a formal equation of how good a layout is at displaying a clustering because it depends on what "clustering" means.

GESTALT, CLUSTERS, AND HAIRBALLS: EYE-TOPOLOGY MISALIGNMENT[17]

In this section, I propose an example-based exploration of the Gestalt approach to the semiotics of a network map. My argument is essentially visual. I show that Gestalt theory helps theorize the visual mediation of network maps and identify the distortions it brings (for an overview of Gestalt theory, see Wagemans et al., 2012; on Gestalt and network visualization, see Bennett et al., 2007; Kobourov et al., 2015.

17 This section was republished on my research blog in a slightly reworked version as a post titled "Hidden structures in hairballs, and how to see them." https://reticular.hypotheses.org/1809

When it comes to network visualization, the most important Gestalt principle is perceptual grouping. “Historically, the visual phenomenon most closely associated with perceptual organization is grouping: the fact that observers perceive some elements of the visual field as ‘going together’ more strongly than others” (Wagemans et al., 2012: 9). Multiple factors influence what we perceive as groups, but two of them stand out in our situation: proximity and closure. In short, you may perceive a set of dots more or less as a textured shape (Figure 33), provided that they are distributed homogeneously, that the contour draws a recognizable shape, and that these shapes are well separated. Technically, your perception works the other way around: you associate the dots because they are close, and this interplay of proximity and distance makes you see a contour, which you then associate with a known shape. This process is not perfect, however. The shapes

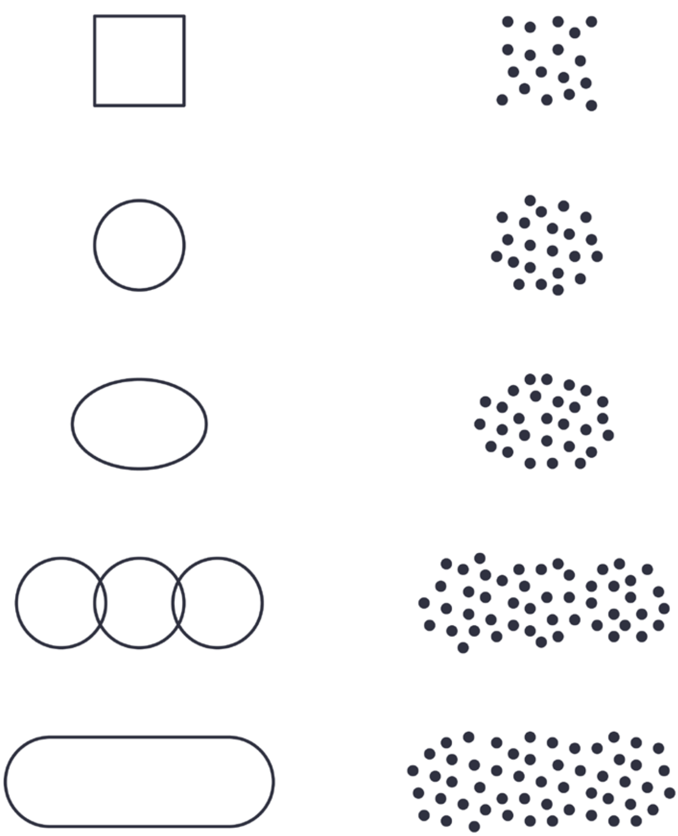


Figure 33: A homogeneous distribution of dots can be perceived as a group with a given shape. These shapes may be ambiguous and perceived differently by different persons.

we see have some degree of ambiguity, and different people may perceive different groups.

These principles are relevant to the topological interpretation regime of networks. Indeed, the topological structure is mainly mediated by the node placement, to the point that some authors propose not to display the edges at all (Noack, 2007b). Here, I will simplify the problem by considering that nodes are represented by dots of the same size and color. Size and color are known visual variables (in the sense of Bertin, 1967) but also influence the perception of groups (Wagemans et al., 2012) and should be accounted for in a complete perceptive model of network maps. Here, however, I only touch on this subject. My main concern is our perception of node groups, which we intuitively interpret as topological clusters. Gestalt theory provides tools to discuss this intuition.

As a starting point, let me emphasize the importance of gaps in our perception of groups. Gaps are places where the continuum of proximities breaks. We see groups when (i.e., because) there are gaps between them. We need gaps to separate clusters visually (Figure 34). If the gaps are too small or inexistent, we do not perceive different groups. Different persons will agree more easily on the groups with big gaps than those with small gaps. Big gaps make visual groups less

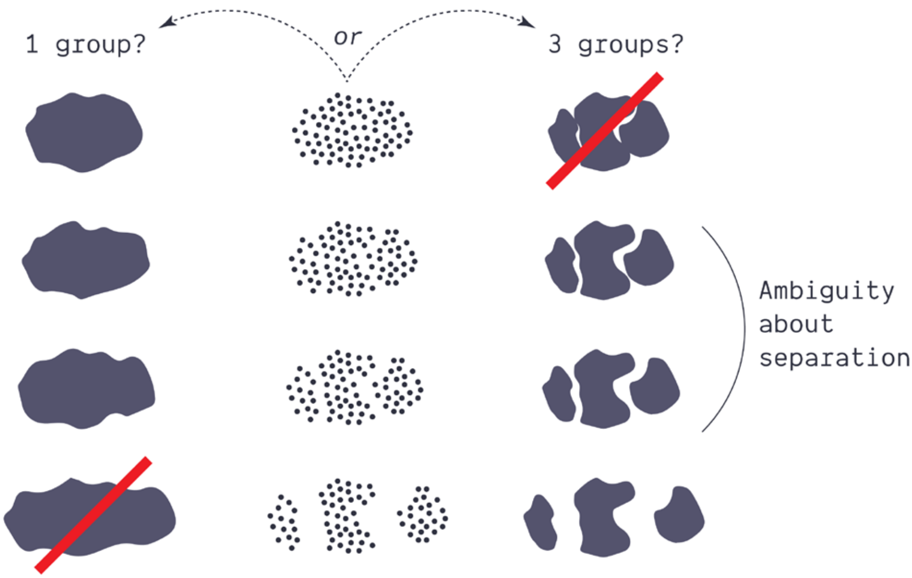


Figure 34. The same set of three groups of dots may be perceived as one if they are close enough.

ambiguous and easier to see. According to Gestalt, this is how our cognitive system works.

Unfortunately for us, the node-placement computations do not follow the same principles as those relating to human vision. Although a force-directed node placement algorithm makes, in some sense, groups, it does not concern the same gaps. Intuitively, the eye looks at the gaps from border to border, while the algorithm concerns the distance between the middle points, between statistical averages (Figure 35). When there are large gaps, the eye and algorithm agree. However, when the gaps are small or inexistent, it is possible that the algorithm "sees" a gap where the human eye does not.

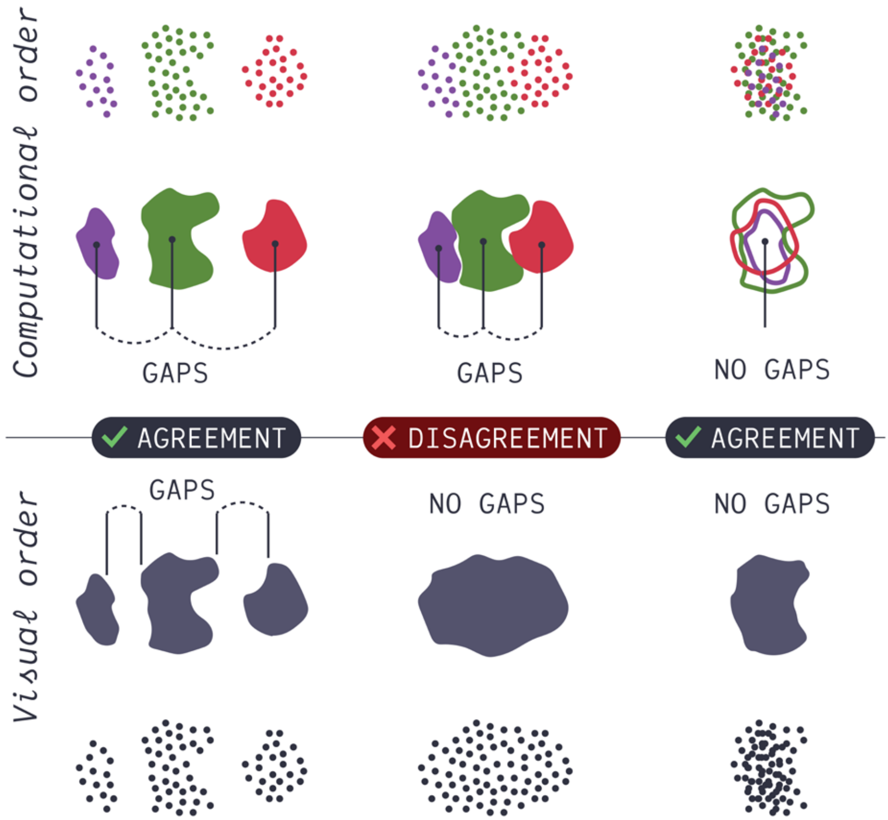


Figure 35. A visual intuition of the disagreement between the algorithm and the eye. Human vision looks at borders, while the algorithm deals with barycenters.

As an experimental illustration of this phenomenon using networks, I will use a *planted partition* model, also called the *stochastic block model*. Here, I build a network with two groups of nodes and create links between the nodes by following a statistical rule. For two nodes in the same group, I will create a link with a probability P_{in}. For nodes in different groups, I will use a probability P_{out}. As long as P_{in} is bigger than P_{out}, each group is promised to be a cluster in a topological sense (e.g., modularity). I choose P_{in} and P_{out} so that P_{in} is smaller and that the sum always equals 100%. As a consequence, P_{in} determines P_{out}. When P_{in} is large (which makes P_{out} small), the clusters are well-defined. When P_{in} is 50%, the community structure disappears completely, and we end up with a random network (in this case, $P_{in} = P_{out} = 50\%$).

I generate a series of networks with a decreasing probability P_{in} (Figure 36). As expected, the most separated groups topologically (P_{in} high) are the most separated visually. As P_{in} gets closer to 50%, the two groups start to merge. At 70%, the general contour starts to look like a circle, but there is still a gap. At 60%, there is no longer a gap. However, there is still a topological structure. Indeed, the layout correctly positions the nodes in the right group; but the groups are stuck to each other. We still see the groups because they have colors, and we would not perceive a cluster just from the node positions. Gestalt theory explains this: we need gaps and contours to perceive groups.

You may think that at a P_{in} of 60%, the two groups are too entangled to be considered distinct. There is some sense to this point, but it does not change that there is some topological structure and, more importantly, that the force-directed layout is able to display it, even though we do not see it. It displays it in the sense that nodes of the same group are placed next to each other. The layout algorithm is so consistently successful at retrieving these groups (Figure 37) that we cannot deny their existence. However, we do not see it because there is no gap. Here, I only give a visual argument, but we could quantify it.

You may also think that we actually see the two groups, even without the colors. Using solely the node placement, take your chance at making the distinction between a planted partition of $P_{in} = 60\%$ and a random network in Figure 38. I doubt you can see any gap, without which, the groups do not appear. Nevertheless, it does not mean that there is no local clustering: close nodes may still be, on average, more connected.

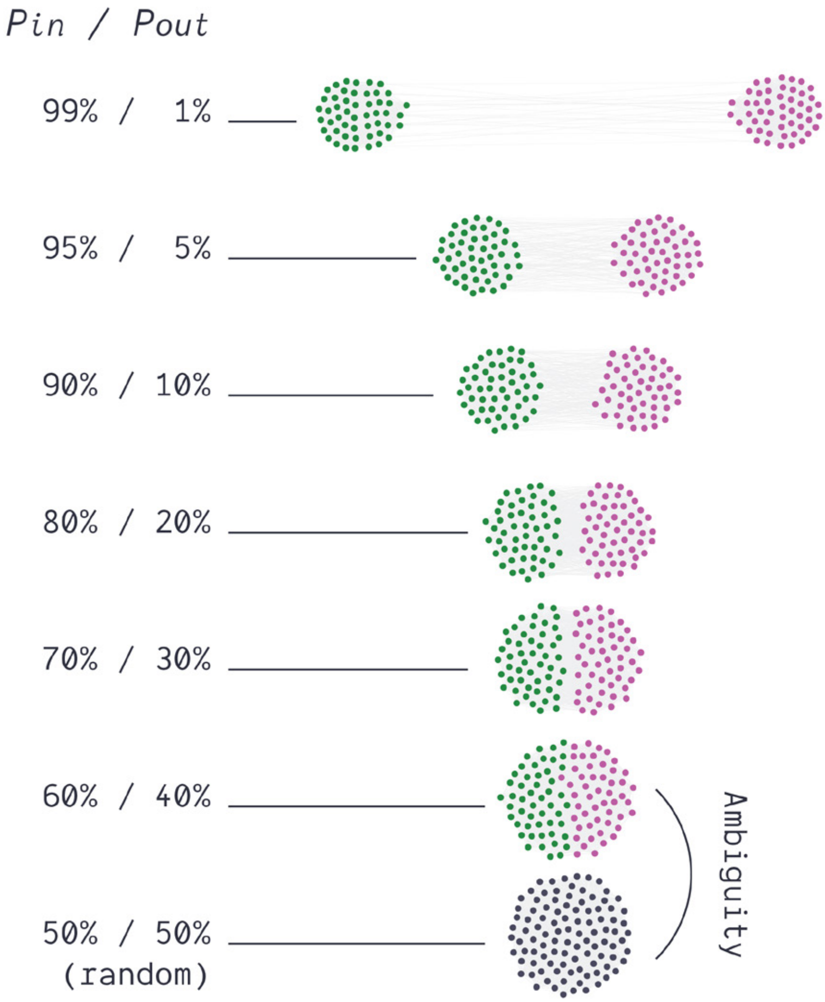


Figure 36: Planted partition networks: nodes in the same group have P_{in} chances to be connected; nodes in different groups have P_{out} chances. Each group has a distinct color. The most separated groups topologically are also the most separated visually. But when P_{in} is low, the node placement does not display a gap. Layout: Force Atlas 2, default settings.

HIDDEN STRUCTURES IN HAIRBALLS

Many authors have blamed network visualization, notably force-directed networks, for producing *hairballs* (e.g., Correa and Ma, 2011; Munzner, 2014; Van Den Elzen and Van Wijk, 2014). Hairballs are typically networks, such as those portrayed in Figures 37 and 38, with a "significant node occlusion and link crossings that can almost completely fill the inter-node space" (Edge et al., 2018:

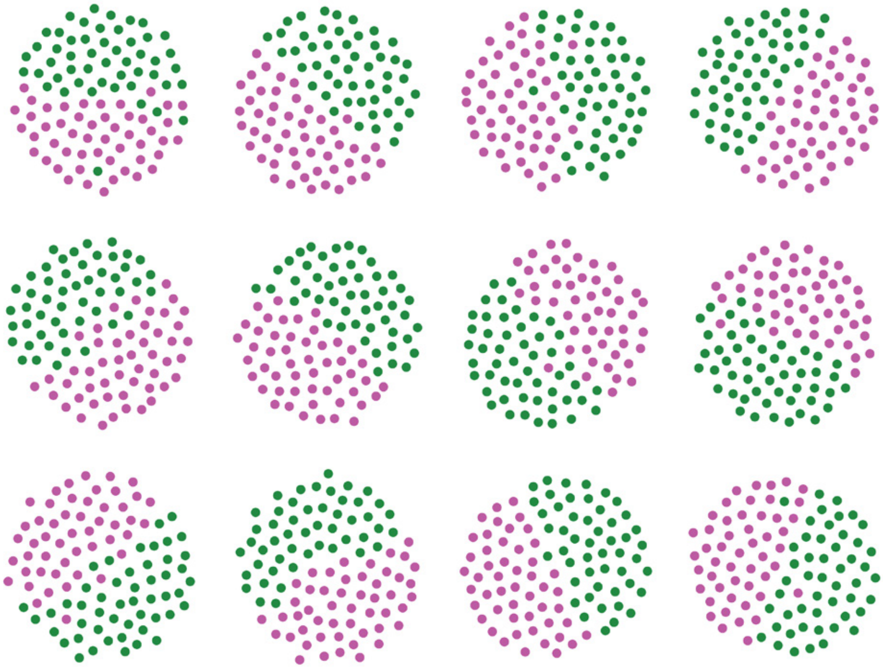


Figure 37: Planted partition networks with P_{in} = 60%. Layout: Force Atlas 2, default settings.

3951). Nocaj et al. (2015) and Edge et al. (2018) proposed a sparsification approach based on a reduction to subgraphs in order to tackle this specific problem, while Dianati (2016) proposed a pruning approach. I do not deny the practical problem of hairballs (lack of visual pattern in the placement), and I certainly think that sparsification methods have applications. However, the hairball is most often a strawman.

The one-page website, hiveplot.com, which promotes an alternative visualization to force-directed placement (Krzywinski et al., 2012), mentions the term "hairball" 31 times, with arguments such as the following:

> *You can already guess that nothing with the name* hairball *can truly be useful. In general, they are not. These views are at best accidentally informative, and cannot be relied upon to consistently reveal meaningful patterns. … Hairballs turn complex data into visualizations that are just as complex, or even more so. Hairballs can even seduce us to believe that they carry a high information value. But, just because they look complex does not mean that they can communicate complex information. Hairballs are the* junk food

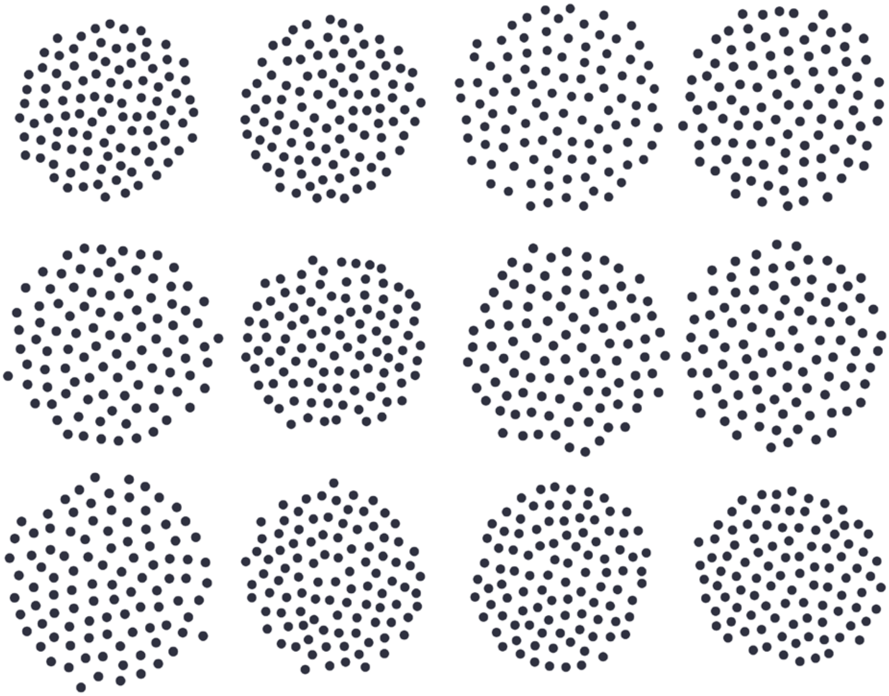


Figure 38: Six of these networks are planted partitions with P_{in} = 60%, and six are random networks with a connection probability of 50%. Layout: Force Atlas 2, default settings. Answer: the random networks are, in reading order, 3 to 5 and 7 to 9.

> of network visualization — *they have very low nutritional value, leaving the user hungry. (emphasis in original, Krzywinski, 2011)*

The hairball rhetoric is easy to track in the academic literature, since it quite precisely employs the term "hairball." The argument is always to blame the layout for failing to represent the structure. However, this statement is never grounded in a model of how we perceive network maps; instead, it relies on a series of assumptions. It assumes that network maps are, to some extent, self-evident. It assumes that the (community) structure is translated by the layout as visual groups and that the lack of visible groups is a shortcoming or a dysfunction. These assumptions have to be re-examined. As we have seen, the layout does not exactly translate the structure as visual groups but as a visual proximity. The difference is the presence of visual gaps: the layout may place same-cluster nodes together in a way that produces no visual gaps, which makes these groups invisible to the human eye.

The hairball rhetoric assesses the algorithm from the outside, using criteria alien to its own functioning. It judges groupings according to the rules of human vision, while the algorithm enforces rules of proximity. The hairball problem partially arises from a misunderstanding about the internal logic of the algorithm. In this section, I endeavor to translate between the inside perspective and the outside perspective on the algorithm's actions. More generally, the rest of this chapter will engage increasingly closer with the computational issues as I articulate the subtleties of force-driven layout algorithms. By claiming that there are hidden structures in hairballs, I reclaim the right to a description of the community structure from the perspective of the algorithm. Us humans might not see the structure, but if the algorithm captures it in its own way, then it means that it is, in some sense, real and that we may capture it another way. It means that the algorithm can teach us something.

First, not all networks make hairballs, assuming that the layout algorithm has been properly parametrized. An excessively high "gravity" setting in Force Atlas 2 tends to produce a hairball regardless of the network's structure: avoid such a setting. If a network is displayed as a hairball, even with low or zero gravity, then it *does* tell something about its structure. It tells that it is pretty dense. You may find the result banal; nevertheless, it discriminates between different structures and mediates the topology. Second, network layouts are not very good at avoiding gaps because, in some sense, gaps do not matter to them. However, they *are* good at placing certain nodes next to each other. It is possible that nodes placed together, i.e., localities, have some meaning. It is possible for clusters to be present, even in the absence of gaps. You may think of it as a bunch of clay balls smashed together (Figure 39): the local structures are still present, but they touch each other. Now, to be clear, not all hairballs hide such structures. However, if we know that they exist, we may check for them. We may reveal them by coloring the clusters: if the hairball has a structure, the colors will not be mixed but gathered in coherent localities. These clusters may be obtained from the data set (categorical node attributes) or from a community detection algorithm, e.g., modularity clustering. For instance, Edge et al. (2018) claimed that hairballs lack "clear separation and grouping." However, in their example (Figure 40 on the left), the hairball has a clear community structure, as manifested the distribution of colors, despite the lack of visual gaps.

In practice, the contour of the hairball may say something about the internal clustering. In Figure 41, the classic network *C. Elegans* (Watts and Strogatz,

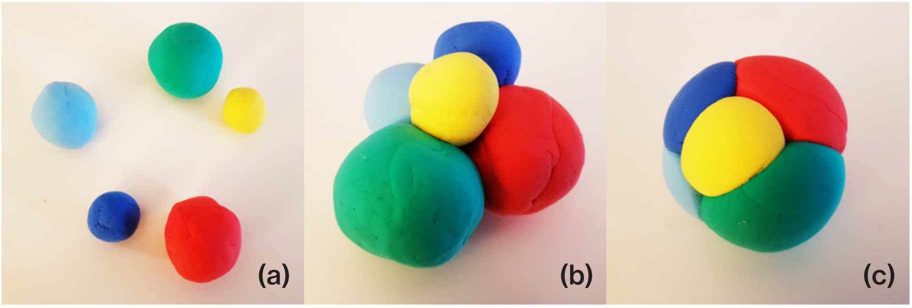


Figure 39: A metaphor for hairball networks: there may be clusters, but they are smashed together like plastic clay balls.

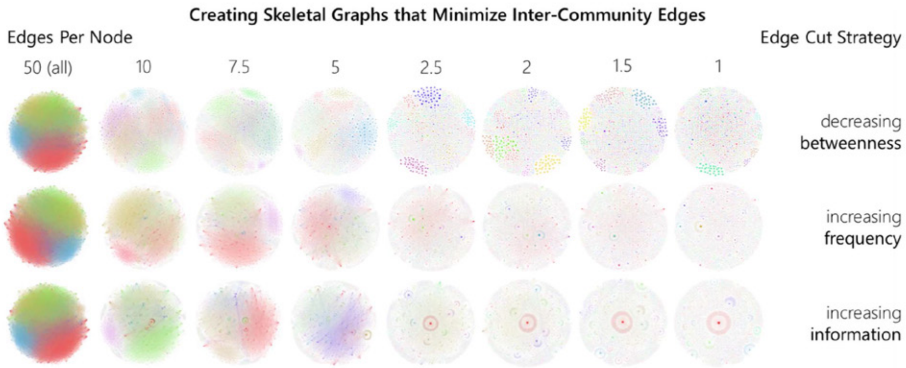


Figure 40: From left to right, the pruning of hairballs, using the layout Force Atlas 2, as illustrated in Edge et al. (2018, Figure 2). "How skeletal community structure emerges from an initial 'hairball' graph." Despite the claim that hairballs display no structure (left column), the presence of color patches demonstrates that the node placement manifested an assortative structure (similar nodes tend to be connected). © 2018 IEEE.

1998) is spatialized by the LinLog energy model. As there are no clear gaps, we do not perceive distinct groups in the node placement (Figure 41(a)), unless we add additional information, such as color (Figure 41(b)). The relatively homogeneous distribution of nodes is perceived as a weirdly shaped stain (Figure 41(c)), the shape of which mediates the topology, even in the absence of clear groups. Intuitively, some denser groups of nodes may pull the network in different directions under the action of the algorithm. This stretches the contour in certain directions and may create bumps and headlands in specific directions. Intuitively, these are partial clusters that create distinct localities despite being interlinked (hence the absence of visual gaps). I offer no proof of this statement here, but you can check in the example below that the clusters found by modularity

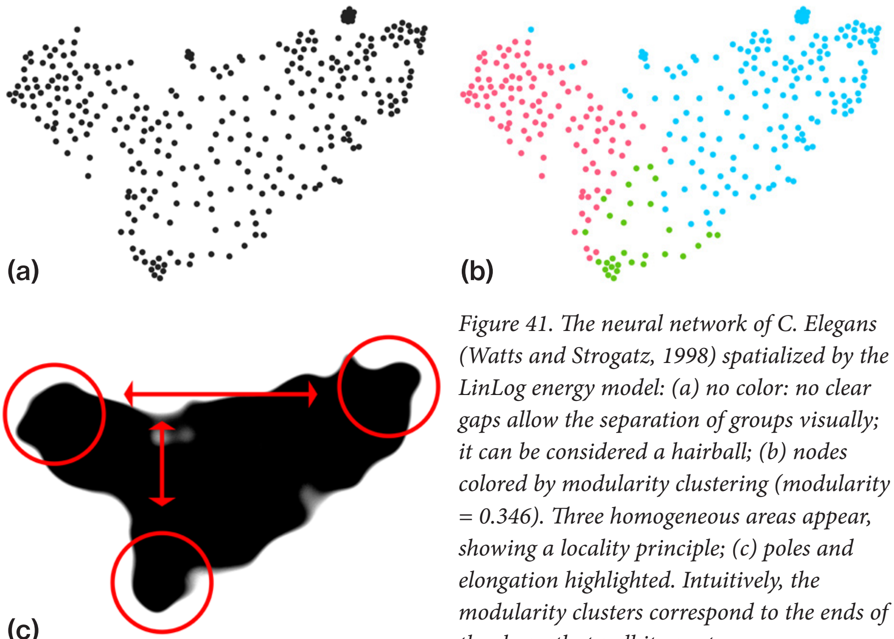


Figure 41. The neural network of C. Elegans (Watts and Strogatz, 1998) spatialized by the LinLog energy model: (a) no color: no clear gaps allow the separation of groups visually; it can be considered a hairball; (b) nodes colored by modularity clustering (modularity = 0.346). Three homogeneous areas appear, showing a locality principle; (c) poles and elongation highlighted. Intuitively, the modularity clusters correspond to the ends of the shape that pull it apart.

maximization (the colors in Figure 41(b)) match the network's elongation and the protrusions of its contour (Figure 41(c)).

I propose calling these pseudo-clusters "poles" because they produce a polarization of the network (Figure 42). The lack of visual separation is meaningful: poles are not only linked; they are also weakly separated. A number of nodes lie in-between the two poles, creating an ambiguous area with no clear divide. The poles themselves, however, may be sufficiently dense to be considered topological landmarks. From a clustering perspective, one may say that each pole strongly defines a weakly delineated cluster. The existence of the cluster is robust, but its limits are ambiguous. The pole itself, however, acts as a local anchor. In Figure 43, the same community detection algorithm (Blondel et al., 2008) was applied to the same network (same as Figure 41). I used the Gephi implementation, which is non-deterministic (Lambiotte et al., 2008). You can observe that the poles always end up in the same distinct clusters but that the boundaries between them are not stable. The existence of clusters around the poles is stable, but their boundaries are not. In other words, each denser zone on the side is non-ambiguously local, but most of the nodes in the middle are ambiguously connected to the different poles.

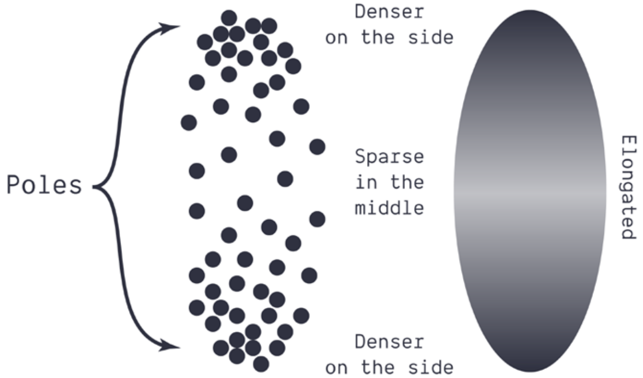


Figure 42. Poles are weakly separated clusters that one can detect by looking at denser areas on the sides of a network spatialized by a force-driven algorithm.

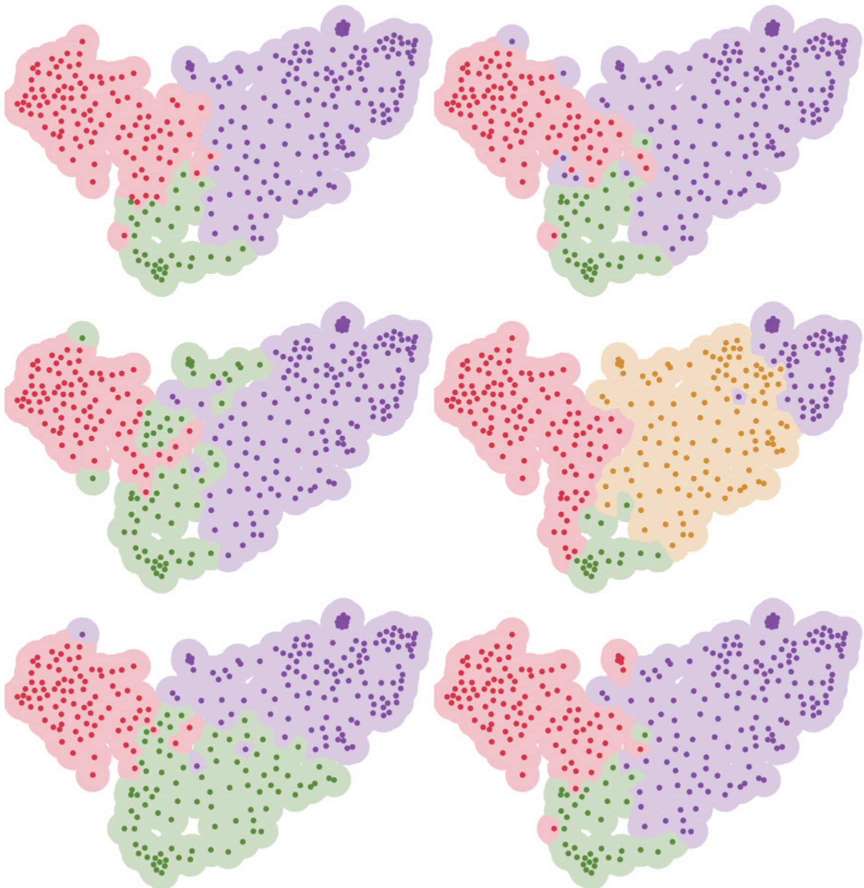


Figure 43: Six renditions of the same community detection algorithm. The poles consistently end up in different clusters, but the boundaries are not stable. Note: one rendition found 4 clusters, contrary to the others. Network: C. Elegans spatialized by LinLog.

In “What Do We See When We Look at Networks?”* we argue that the ambiguity of this middle space is a feature of the data. The absence of visual gaps reflects the absence of a clear boundary in the topology. In any event, the community detection algorithms are tasked with finding a boundary and reacting to the lack of natural gaps in the topology, with a high variance in where they place the limit. From an interpretative standpoint, these boundaries do not deserve much trust because they are somewhat arbitrary. Therefore, we argue that the layout is a better reduction of the topology, which more faithfully reflects the inherent ambiguity of clustering. This assumes that we know how to interpret the layout, of course. Further, while it does not undermine the usefulness of clear-cut categories in various situations where ambiguity is a problem, it is essential to realize that clusters are not separated things; they are poles in a continuous and ambiguous landscape of link density.

Now that we are equipped to understand clustering as, more generally, a matter of locality, we can start finding structures in hairballs. Although the lack of visual gaps prevents us from immediately seeing clusters, we can rely on the subtleties of the contour and the denser zones on the borders. Hairballs may have non-obvious poles. As a test, we can run a modularity clustering a few times to check whether, and where, it is consistent. This approach reveals a community structure in some networks (Figures 44 and 45) but not in all (Figure 46). Noteworthy, in this visual experiment, I used the same settings for the community detection algorithm, and I used consistent colors. However, the number of clusters depends on the settings I used, and it also varies independently.

WHY THE LINLOG DOES NOT EXPLAIN WHAT WE SEE IN NETWORKS

At this point, you may wonder “didn’t Noack (2009) quantify precisely what we see in networks? Didn’t he prove that force-directed layouts display clusters?” The answer is “no.” In short, his work only shows that the techniques he uses tend to separate clusters visually. His argument is that visual cluster separation provided the direction of his algorithm, but it did not allow him to assess the resulting placements in practice. In this section, I reveal the three justifications that Noack provides for his statement that the LinLog separates clusters; I expose their contradictions, and I show why they are not really about the result (the layout) but how it is produced. That said, I do not claim that the LinLog is bad (it is great!) or that Noack’s point is useless. I only highlight the fact that his justifications do not

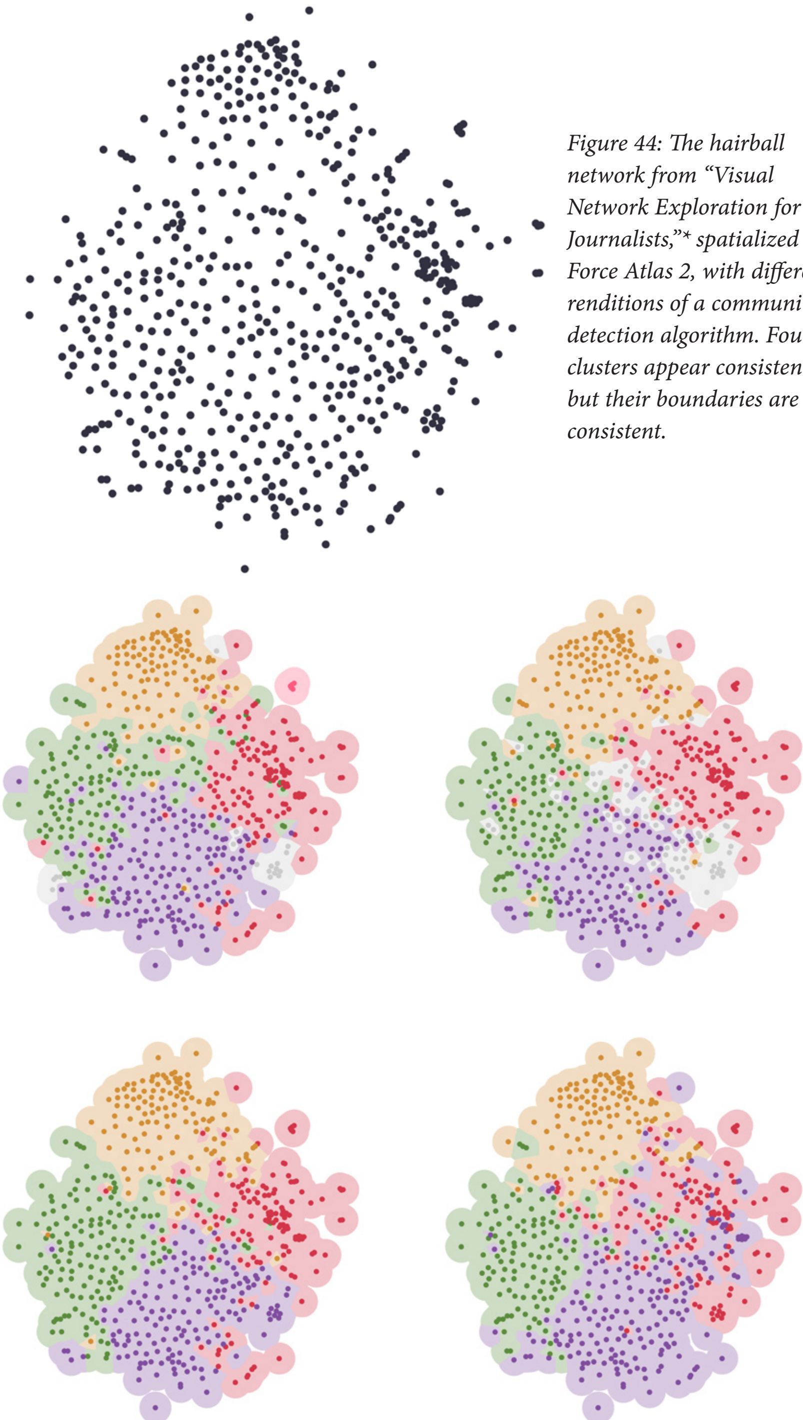
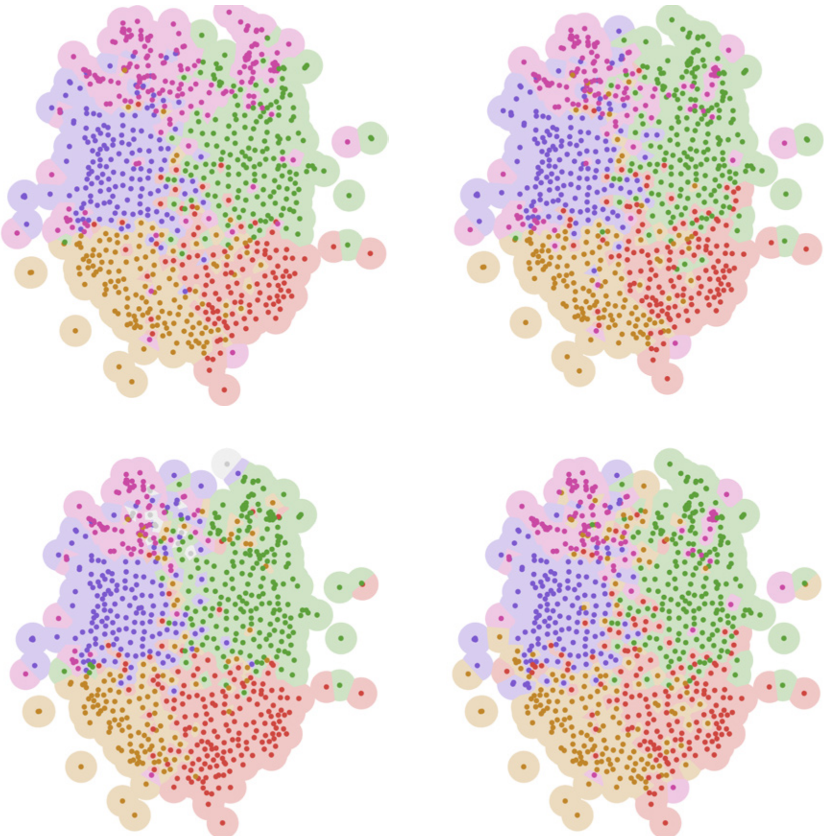


Figure 44: The hairball network from "Visual Network Exploration for Data Journalists," spatialized by Force Atlas 2, with different renditions of a community detection algorithm. Four main clusters appear consistently, but their boundaries are not consistent.*

Figure 45: The hairball network from Cardon et al. (2019), spatialized with the LinLog energy model, with different renditions of a community detection algorithm. The same clusters appear consistently, but their boundaries are not consistent.



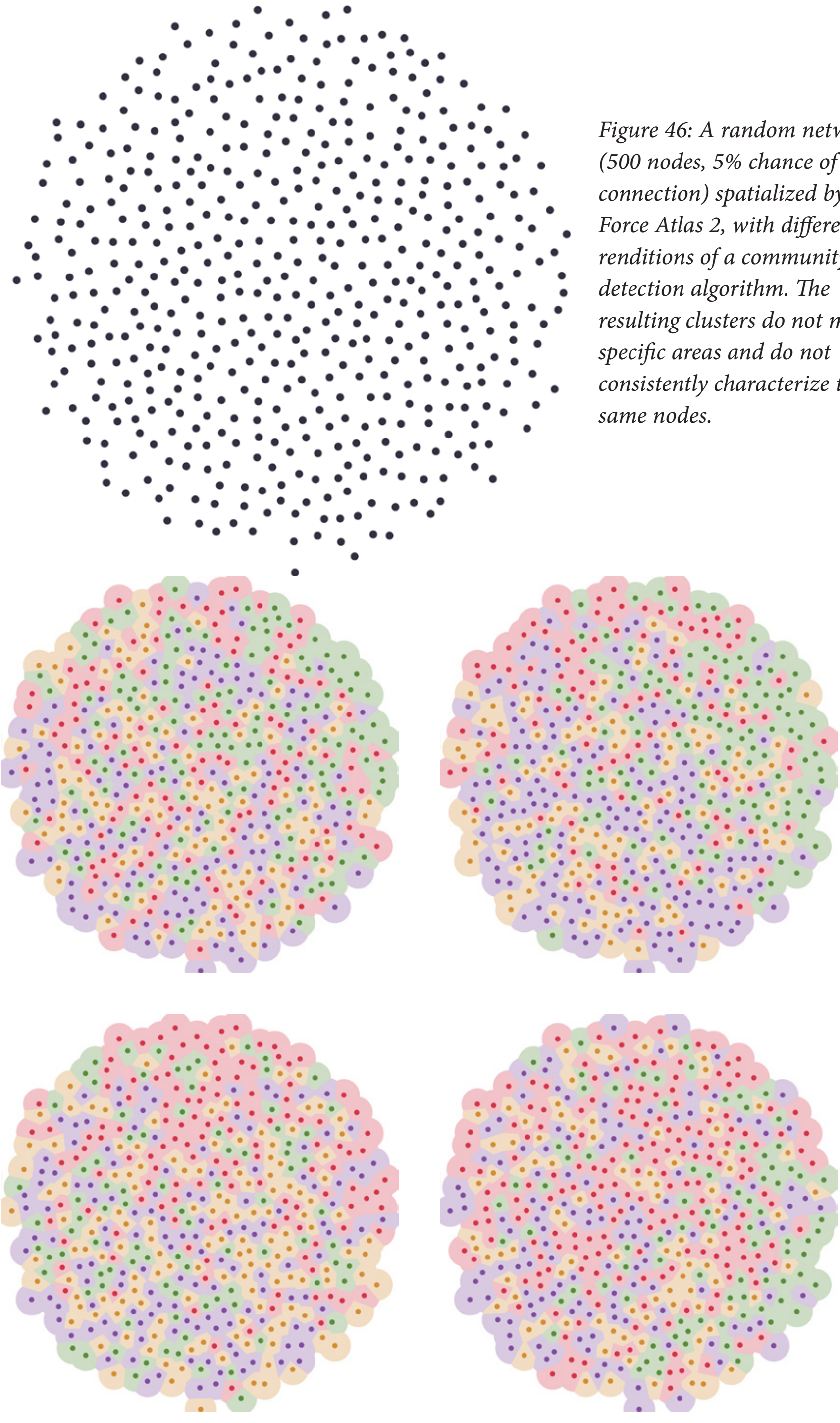


Figure 46: A random network (500 nodes, 5% chance of connection) spatialized by Force Atlas 2, with different renditions of a community detection algorithm. The resulting clusters do not map specific areas and do not consistently characterize the same nodes.

explain why his algorithm makes the community structure visible. To be clear, however, most algorithm designers do not even try.

Noack's quality metric was used to design an algorithm (the LinLog), not to assess its outcome, but the placement itself. Yes, the LinLog places the nodes so that we get a near-optimal value of normalized edge length, but how good is this value? This question is not rhetorical. In practice, the LinLog only does *the best it can*, but this does not mean that the result is *good in absolute*, which is what "optimal" means here. It means that, according to Noack's mathematical argument, the LinLog performs better than other energy models. The assessment is relative, not absolute; "better" does not equate to "good." Moreover, in practice, the better result generally remains *bad*. Bad here means that the normalized edge length remains too high to allow stating that "connected nodes are close." In practice, the quality metric does not allow one to interpret the layout. In general, many connected nodes are *not* close to each other, and it is easy to observe: they are the ones connected by the long edges in Figures 47 and 48. Indeed, Noack's quality metric aims to produce short edges overall (notwithstanding normalization). In other words, the layout aims to put connected nodes next to each other. When this fails, we have a pair of nodes that are distant yet connected, thus producing a long edge. Surely, other energy models do even worse, but this information is not useful to interpreting the resulting placement. We simply cannot say that the LinLog puts connected nodes together. It does for some but not for all. When the network has a strong community structure (Figure 47), there are fewer long edges. Noteworthy, although the example of Figure 47, which visualizes the network from my preliminary example (Figure 5), has a remarkably strong community structure, one in five edges remains longer than average. When the network has no community structure (Figure 48), then most edges are actually quite long. In the next chapter, my first tinkering will address this specific problem.

There is another issue with the interpretation of the LinLog, which is connected to the previous one and more subtle to grasp. Noack's (2007b) argument about the "separation" between clusters relies on three factors: (1) it comes from minimizing edge lengths; (2) it is improved by the "edge repulsion" trick; and (3) some energy models improve it too. I believe that the "edge repulsion" is the main factor, even though Noack seems to rely more on the energy model. Let us see how he states each justification.

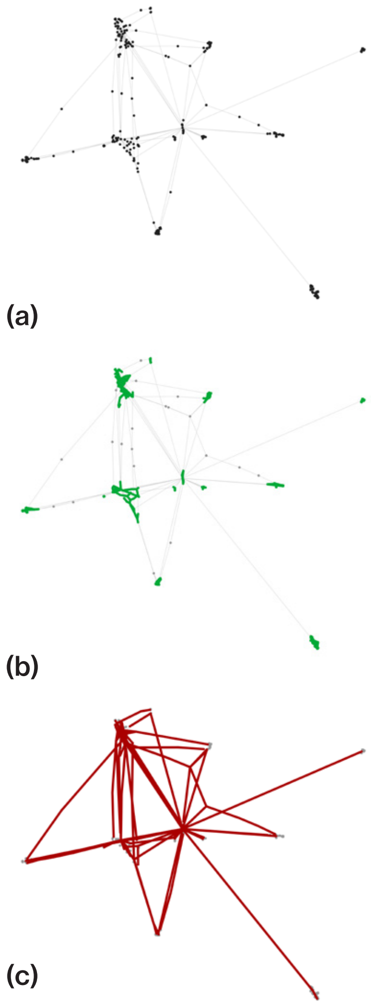


Figure 47. The network of Wikipedia articles on Europe (from Figure 5), where nodes are placed with the LinLog energy model (using the Force Atlas 2 implementation): (a) all edges represented; (b) edges shorter than average are highlighted; (c) edges longer than average are highlighted. Long edges are connected pairs of nodes that were not placed close to each other. Note that even though they represent one-fifth of edges, they are much more visible because they are much longer. The lack of balance between short and long edges is due to the strong community structure of the network.

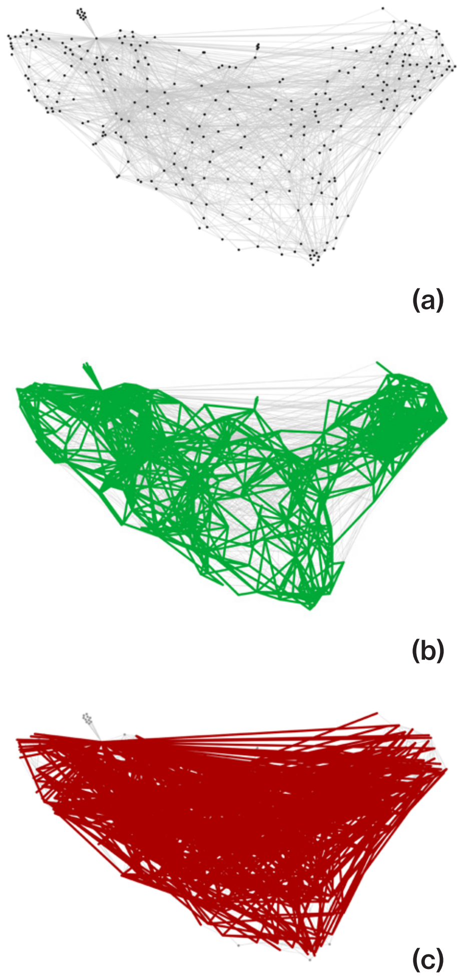


Figure 48. The neural network of C. Elegans (Watts and Strogatz, 1998), where nodes are placed with the LinLog energy model (using the Force Atlas 2 implementation): (a) all edges represented; (b) edges shorter than average are highlighted; (c) edges longer than average are highlighted. Long edges are connected pairs of nodes that were not placed close to each other. Note that the short and long edges are more balanced than in Figure 48 due to the lack of a strong community structure.

JUSTIFICATION 1: MINIMIZING EDGE LENGTHS PROVIDES CLUSTER SEPARATION

> *The most popular energy models … are either similar to stress functions of multidimensional scaling, or represent force systems of pair-wise attraction and repulsion between vertices. … In models of the latter type, adjacent vertices attract, which tends to group densely connected vertices, and* ***all pairs of vertices repulse, which tends to separate sparsely connected vertices****. (Noack, 2009: 1, emphasis added)*

Noack points to an intrinsic difference between algorithms optimizing a stress function (e.g., Kamada and Kawai, 1989; Gansner et al., 2004) and force-driven algorithms (e.g., Eades, 1984; Früchterman and Reingold, 1991; "Force Atlas 2"*). The former seek to produce distances proportional to the geodesic distance (the number of links between two nodes) and are not specifically designed to visualize the community structure, but Noack argues that force-driven algorithms "tend" to visualize it. The design intent can be acknowledged, but as we have seen, in practice, it does not materialize for all edges. In other words, force-driven algorithms "tend" to visualize community structure, but in a weak and imperfect way.

JUSTIFICATION 2: EDGE REPULSION PROVIDES CLUSTER SEPARATION

> *Most existing energy models and force models … have not been designed to find clusters, but to produce readable visualizations. They enforce small and uniform edge lengths, which often prevents the separation of nodes in different clusters. As a side effect, they tend to group nodes with large degree (i.e. with many edges) in the center of the layout, where their distance to the remaining nodes is relatively small. …* ***the edge-repulsion LinLog energy model [is] not biased towards grouping nodes with high degree****, and [is] thus particularly appropriate for graphs with [heavy-tailed] degree distributions, which are very common in practice. (Noack, 2007b: 1, emphasis added)*

Noack states here an important argument against the aesthetic criterion of uniform edge lengths, often defended before the complex network turn (Eades, 1984; Sindre et al., 1993; Di Battista et al., 1994). Indeed, uniform edge lengths prevent the manifestation of the community structure—not by design but as a "side effect." The point is uncontroversial and has been tested experimentally (Van Ham and Rogowitz, 2008). This is, again, about long edges. The crucial point about separation is the presence of edges between clusters. Let us call them "bridges" for simplicity (Figure 49). Intuitively, these edges *have to be long* in order to provide a good visual separation between the clusters. This is why uniform edges conflict with visualizing the community structure. I think that it relates more to justification 3 (energy model) than to justification 2 (edge repulsion), but I relay here how Noack has built his argument.

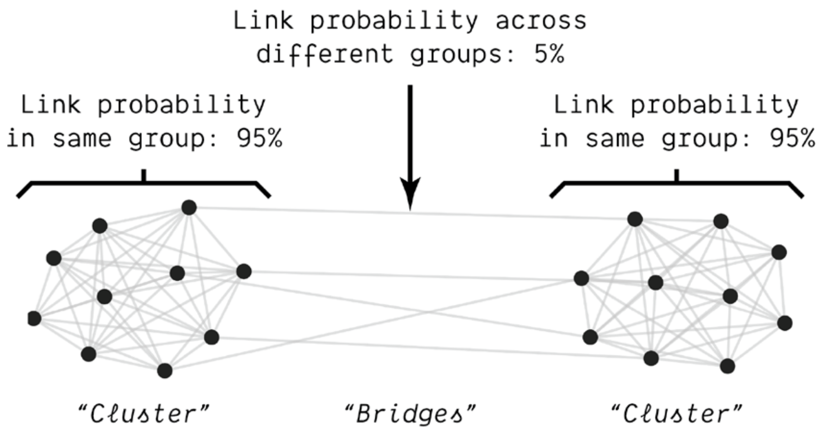


Figure 49. A network generated from a "planted partition" model featuring a community structure by design. Layout: Force Atlas 2. The denser groups can be called "clusters" and the edges between them "bridges." The bridges have to be longer in order to ensure a good visual separation.

Noack's argument focuses more precisely on highly connected nodes. For simplicity, let us call them *hubs*. Noack argues that the "edge-repulsion LinLog" is not "biased" toward grouping hubs (compared to the traditional node-repulsion LinLog). Actually, edge repulsion is not specific to the LinLog energy model, but it can be applied to any energy mode. Noack illustrates this with the figure reproduced here (Figure 50), where he uses edge repulsion on Früchterman and Reingold's (1991) energy model. It illustrates the bias of node repulsion towards the hubs. Noack compares the techniques by showing two star-shaped networks: one centered around a group of hubs and the other around a single node. Node repulsion produces shorter edge lengths between hubs than edge repulsion. Thus, edge repulsion is "not biased towards grouping [hubs]" (Noack, 2007b: 454).

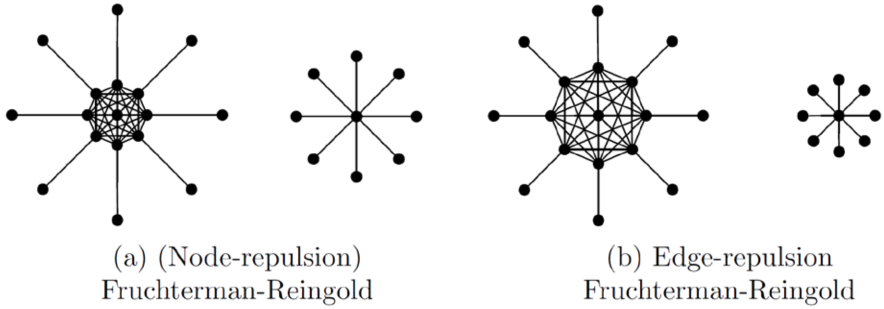


Figure 50. Noack's illustration of edge repulsion on the energy model of Früchterman and Reingold. His visual argument is about comparing edge lengths between situations where nodes have many or few neighbors (Noack, 2007b: 469, Figure 3). Reproduced with permission.

Noack's argument does not require the reader to actually understand what edge repulsion consists of, only to agree that it is less biased toward grouping hubs. However, I found no justification other than the visual argument of Figure 50. The principle, in itself, is no mystery: "In the *edge-repulsion LinLog energy model* the repulsion between nodes is replaced with repulsion between edges" (Noack, 2007b: 461). Nevertheless, there is a catch because, in practice, "the repulsion does not act between entire edges, but only between their end nodes" (p. 61). As a consequence, "the node-repulsion LinLog energy of a layout equals the edge-repulsion Lin-Log energy if the weight of each node is its degree" (Noack, 2007b: 469). In other words, although there is some elegance in presenting the technique as "edge repulsion," all it boils down to is actually reinforcing repulsion for hubs by multiplying the force by the degree.

This less dramatic formulation has turned out to be a pretty common idea. For example, the technique is suggested by Gansner et al. (2004: 245), whose algorithm is not even force-directed: "Setting desired edge lengths to a uniform length (typically 1) inevitably makes the neighborhood of high degree nodes too dense in the layout. Consequently, we suggest weighting edges by their neighborhood size." I also unknowingly reinvented this technique when I tinkered with Force Atlas 2. I reflected that a network would be more readable if non-hubs were placed close to their hub neighbors, which could be captured by the product of degrees. Thus, Force Atlas 2 is based entirely on edge repulsion, whether the LinLog energy model is used or not. This point and the equations it refers to are featured in the paper "Force Atlas 2,"* and we suggested at the time that edge-reduction might have more impact on the result and its readability than the (attraction, repulsion)-model.

Finally, it is worth mentioning what Noack calls here "the many real-world graphs with right-skewed degree distributions" or, in the language of this dissertation, hub-rich empirical complex networks. Indeed, Noack proposed his algorithm at a turning point when network visualization practices were shifting to large empirical complex networks. As he appropriately remarked, node repulsion is particularly bad at dealing with such networks, precisely because it fails to separate the hubs. From my own practical experience, edge-repulsion algorithms indeed provide much more usable results. As a side note, the problem is not only about placement but also convergence: hubs tend to "swing" violently during simulation, which prevents them from converging correctly (we develop this point in "Force Atlas 2"*).

In conclusion, edge repulsion mitigates a nefarious side effect of hubs flocking to the center of the layout and has a very visible impact in practice. Beyond this, however, Noack does not explain why a good separation between clusters is favored.

JUSTIFICATION 3: THE LINLOG ENERGY MODEL PROVIDES CLUSTER SEPARATION

The third argument is the object of an entire paper: "Layouts with optimal energy are relaxations of, and are thus consistent with, clusterings with optimal modularity" (Noack, 2009: 1). In short, certain energy models are mathematically equivalent to modularity clustering. In a certain number of dimensions, and for certain combinations of attraction and repulsion, their resulting node placement is "consistent with" clusters if by cluster we mean the characterization given by modularity, often interpreted as a "community structure" (Newman, 2004).

Noack reflects on a minimal case of two triangles connected by an edge or a path of length 2 (Figure 51(a)). Note that this case is a minimal version of the bridged clusters of Figure 49: the visual separation of clusters depends on edge lengths in different situations. Each combination of attraction and repulsion defines a different energy model, and Noack reflects on the impact of these two forces on the separation. His analysis is summarized in Figure 51(b). In this argument, the energy model impacts distances in two ways: through path lengths and link densities. These two influences then decide the separation. Noting the attraction force exponent "*a*" and the repulsion force exponent "*r*," Noack shows that the distance between two nodes "depends only on the density, and not on the path length, if a=0 (as in the LinLog energy model), and increases with the path length if a>0"

(p. 3). Furthermore, interpreting his equations "by considering each community as one big [node]," Noack generalizes that "[d]istances are less dependent on densities for large *a–r*" (p. 3). These two arguments are summarized as the two diagonal arrows of Figure 51(b).

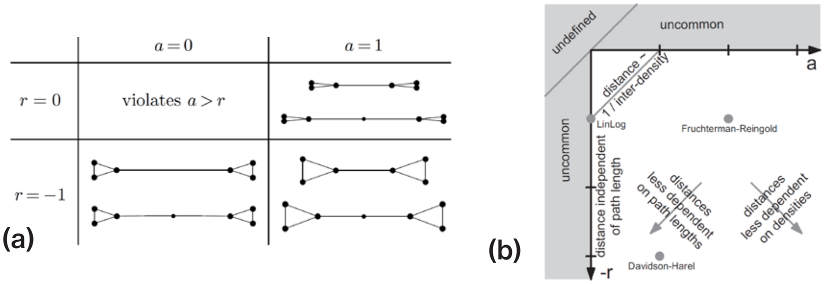


Figure 51. Noack's (2009) visual argument on which energy models provide better separation. The exponent of the attraction force is noted "a," and the exponent of the repulsion force is noted "r". (a) Influence of different (a-r) combinations on a simple cluster-bridge case. (b) The (a-r) space where different energy models can be plotted. Reprinted figure with permission from Andreas Noack, Physical Review E, 79(2), 2009. Copyright 2009 by the American Physical Society.

Noack's argument on the optimal energy model draws on two distinct understandings of separation. First, a good visual separation between clusters means that distances must depend on densities as much as possible (*a–r* must be as small as possible). At the core, clusters are defined by the density of links, so visualizing them must account for this density in some way. Second, the energy model is only equivalent to modularity if distances do not depend on path lengths (*a* = 0), as modularity disregards path lengths. Here, separation is defined by the mathematical equivalence to modularity. Since *a–r* must be as small as possible and *a* must be 0, the absolute best possible energy model has to be *a* = 0 and *r* = -1. An exponent of 0 is (here) a logarithm, and an exponent of -1 is linear, hence the name of this energy model: LinLog. As a side note, the *(a, r)*-energy model of Force Atlas 2 is *(1, -1)*, halfway between the LinLog *(0, -1)* and the Früchterman-Reingold *(2, -1)*. In "What Do We See When We Look at Networks?"* we discuss the three energy models in a practical case (reproduced in Figure 52).

DISCUSSION OF THE JUSTIFICATIONS

So, exactly what does provide a visual separation of clusters? The different justifications require substantial clarification. In particular, as you may have noted,

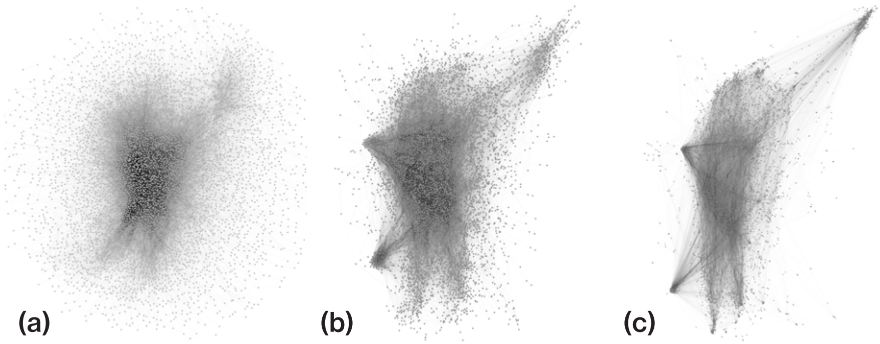


Figure 52. The "jazz network" from "What Do We See When We Look at Networks," spatialized (a) with the algorithm proposed by Früchterman and Reingold (1991), (b) with Force Atlas 2* (with default parameters), and (c) with the edge-repulsion LinLog energy model (Force Atlas 2 implementation).*

there are multiple contradictions. First, minimizing edge length is supposed to improve separation (justification 1), but at the same time, long edges seem essential, at least between clusters (justification 2). Second, edge repulsion makes clusters less dense visually (check, e.g., Figure 50), while we conversely expect *denser* clusters to be more separated visually. Beyond these contradictions, it is worth noting that Noack's argument on the energy model (justification 3) is independent of edge repulsion. His paper (Noack, 2009) makes heavy mention of edge repulsion, but the rationale leading to the conclusion that the LinLog is the optimal energy model is perfectly valid for the node-repulsion version. However, the node-repulsion LinLog does not provide the spectacular separation of the edge-repulsion version, as one can see in Noack's own figures (reproduced in Figure 53).

Noack's work features a more detailed rationale about the interpretive properties of force-directed layouts than any other similar algorithm design, to the point that Munzner (2009, 2014) frames it as a piece of data-visualization evaluation. However, the rationale for visual cluster separation is not fully consistent or as grounded as it may seem at first glance. Noacks' thesis (2007a) and papers (2003, 2007b, 2009) are not technically wrong, but their conclusions must not be over-interpreted. His remarkable and decisive work tells us that different algorithmic techniques contribute, to some extent and in their own ways, to separating clusters visually. However, it does not tell us where visual separation comes from. It suggests different causes, but it does not rule out other influences, and Noack actually acknowledges that it could arise as a "side effect" (justification 2; Noack, 2007b). At the end of the day, providing visual cluster separation was a direction that helped Noack build a great algorithm; it was not a statement that defines the resulting layouts or allows for assessing them.

WE CANNOT TELL WHAT WE SEE WHEN WE LOOK AT NETWORKS

Different algorithms answer different needs, aim to arrive at different kinds of results, and succeed at different degrees, all with different side effects. Früchterman and Reingold (1991: 1133) “would like the [nodes] to be uniformly distributed in the frame,” while stress-minimization methods are aimed at approaching defined edge lengths (Kamada and Kawai, 1989; Gansner et al. 2004), and Noack’s (2009) LinLog prioritizes “faithful representations of the community structure” (p. 5). No algorithm is indisputably better than the other because they are all aimed at different things. They are optimized for different criteria and have different understandings of what a successful layout is.

Before the turn to complex networks, networks were mostly diagrams, and reading them was a matter of accessing the signs in good conditions. The goal of aesthetic criteria was to prevent visual cluttering and organize the signs for tasks such as following the paths. After the turn, most network maps qualified as big data visualizations that we interpret by inquiring into emergent visual patterns. There are too many edges to follow the paths, and node placement has become the most important feature. The question of readability remains (Dunne et al., 2015; Munzner, 2014), but it is no longer sufficient to allow an interpretation, as the need for mediating the topological structure has become central (Brandes and Wagner, 2004; Correa and Ma, 2011; Soni et al., 2018).

When we see a network map (e.g., Figure 5), even if we perceive patterns, we cannot interpret the node placement without knowing the algorithm used to produce it and its settings. A trained eye could make an educated guess on the algorithm employed, but this practice is, at best, a stopgap. We assume that the unsituated network maps we see were produced by a force-directed algorithm (or similar), and we intuitively seek community structure and core–periphery relations, but this is a risky practice, of course. What the algorithm employed tried to optimize is, obviously, an important piece of context. For example, one should not pay too much attention to clusters in a stress-minimization layout, as this is not what the algorithm aims to make visible. Moreover, judging the placement from the way it was produced is a compromise. Ideally, we should be capable of

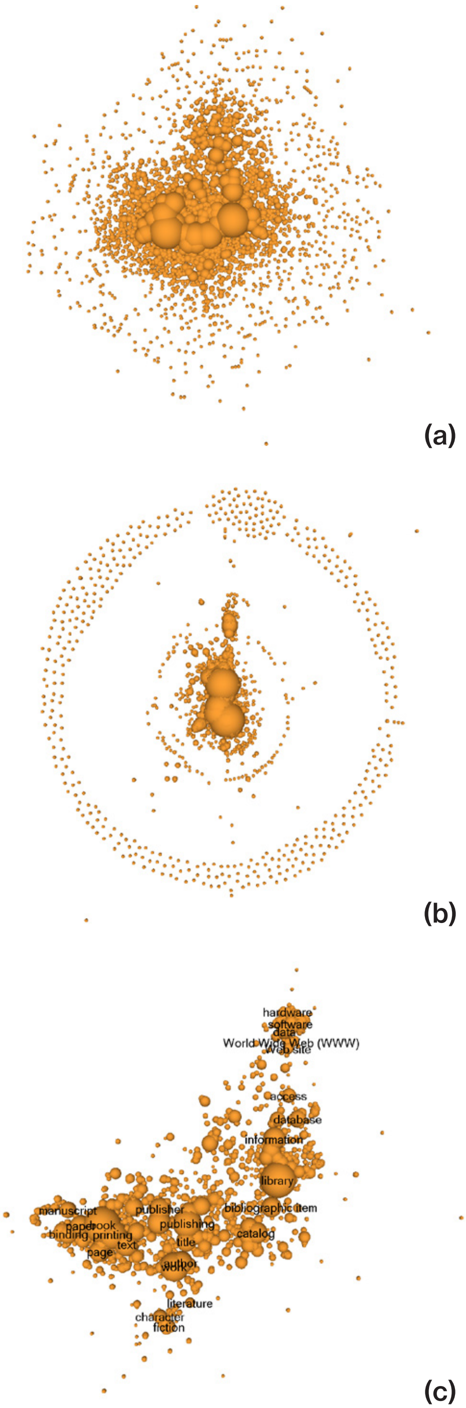


Figure 53. Three renderings of the same network (Noack, 2007b: Figure 7). The links are not pictured. Früchterman-Reingold (a) does not offer a good visual separation. The node-repulsion LinLog (b) does not provide as good a visual separation as the edge-repulsion LinLog, (c) intuitively, because poorly connected nodes take up too much space.

judging the layout on its own—if only for one reason, it is because of the massive side effects of these algorithms.

Knowing the layout algorithm and its settings is not enough. As I have argued about the LinLog, the intent of the algorithm does not suffice to assess the resulting node placement. The same is true, *a fortiori*, for the other algorithms. Indeed, most algorithms only express functional principles, and it is difficult to relate them to the resulting layout. Furthermore, even when an algorithm states a quality metric that we can relate to the visual, such as the LinLog, it is not guaranteed that this metric will capture the relevant aspects of the resulting layout. In short, functional principles provide no consistent model of what a force-directed layout displays. Consequently, when we see a pattern in a network map (e.g., a cluster), we cannot explain where it comes from. We know perfectly well how each algorithm functions, but the same way the shape of dunes is not written in the equations of thermodynamics, the functioning of a layout algorithm does not help us understand the visual patterns it produces. The pattern emerges from interactions. The mathematical assessment of interpretability proposed by Noack (2007b, 2009) was a considerable advance in the right direction, but it did not mark the end of the road.

Our inability to trace the pattern is an issue in a scientific setting. The robustness of a scientific statement depends on our ability to navigate through the chain of mediations (Figure 13 in Chapter 2) between that statement and the materiality it refers to (Latour, 1999). The most productive way to situate a network map in a scientific setting is to make visible how it refers to empirical reality or, at least, to the data. It allows a discussion of the methodology and helps with reproducibility. In the absence of an explicit relation between what we see in a network map and the relational data it represents, we cannot fully justify what the image pictures. Nevertheless, as we have seen, exploration (EDA) does not require it.

A possible message about VNA could be to restrict it to exploration and always provide evidence with statistical metrics. I pushed this approach in many Gephi workshops, but it does not account for the fact that force-driven layouts are somehow good at mediating the topological structure. In practice, Gephi users *trust* the layout or, more radically, see it as self-evident. I believe that this comes from the layout's consistency, its ability to produce certain patterns reproducibly, even though we do not know how to quantify this consistency. This trust tends to legitimize VNA as a research practice insofar as the research community's agreement about seeing the same patterns, despite the lack of quantification. This is not what I suggest; it is what I observe. I would not say that VNA has become an academic standard, but as Bruns (2013) remarks, many academic authors feature network maps in their publications without mentioning the algorithm used and its settings, as if they were self-evident images. "Neither, it should be noted, do the referees for articles on [social media] usually request such methodological information: treatment of tools such as Gephi as black boxes whose interior operations can be ignored is not limited to scholarly authors alone" (Bruns, 2013). We account for more practices of this kind in "Unblackboxing Gephi."*

Limiting VNA to exploration still creates an epistemic surplus. The case of "Divided They Blog" (Adamic and Glance, 2005) is telling. Even though the authors do not analyze their network map in their article (Figure 2), it is circulated and interpreted by other authors as if it were self-evident (Foucault Welles and Meirelles, 2015). EDA does not prevent story*letting*. Furthermore, the trust-based legitimacy of network maps comes with two major threats. First, this trust could disappear, which would invalidate the scientific knowledge based on it. This sort of legitimacy would make network maps precarious as scientific devices. Second, trust offers too few protections against collective biases. My own experience with network visualization makes me believe that they might be trustworthy, but this is not the point. The point is the extent to which this is the case and who decides it. The datafication of society and the rise of surveillance capitalism have made it clear that we need to scrutinize algorithms and hold them accountable. For the exact same reasons, layout algorithms must be held accountable beyond their possible trustworthiness. Quantifying the consistency of the patterns they produce would at least offer a ground for discussing them. It would contribute to situating them and pushing back against their affinity with self-evidence and the rhetoric of big data.

THERE IS NO SIMPLE AND ACCURATE EXPLANATION TO FORCE-DRIVEN LAYOUTS

A mental model of layouts would be useful to scholars who use network maps. I think of a thumb rule telling which topological feature causes a given pair of nodes to have the distance they have. It does not need more than a reasonable accuracy and to make predictions simple enough to write them in plain English in our publication. For instance, "close nodes are connected," or another reasonably short, explicit sentence would suffice. However, the following sentence is not satisfying: "close nodes result from an attraction–repulsion energy model." Indeed, it only names the construction process; it does not articulate the node distances with the topology. If a simple model was proven true reasonably often for the kind of network scholars study, it could be used as an explanation of force-directed layouts. The model just has to work both ways: from topology to distances and from distances to topology. With Tommaso Venturini, we have promoted the following sentence when teaching: "two nodes are closer the more directly or indirectly connected they are." It is sufficiently understandable and highlights key aspects of force-directed placement, but it remains inaccurate. It tells that node pairs that are simultaneously close and disconnected are, thus, indirectly connected, but what does this mean? Intuitive characterizations, such as a short path length or mean communing time, do not work (as I am about to show). We have seen that force-directed layouts are based on rules (the energy model). It is reasonable to think that these rules can be turned into a simple model. In the next section, I explore the simple models we can draw from the algorithms and why they do not work. My argument is mostly visual and draws on counterexamples. I do not measure systematically how wrong these models are in general. A final clarification for the distracted reader skimming the text thus far: **these interpretive models are all wrong.**

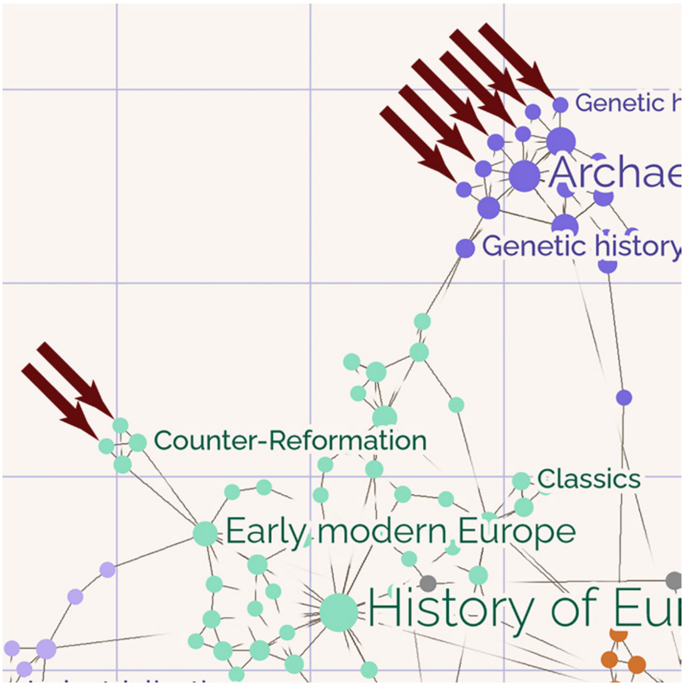
MODEL 1: CLOSE EQUALS CONNECTED

This model is a direct translation of the attraction–repulsion energy model used in any force-directed network: connected nodes attract, while disconnected nodes repulse each other. It also corresponds to the aesthetic criterion of "minimiz[ing] the global length of edges" (Sindre et al., 1993). We have already seen that long edges break that model. However, many disconnected nodes also end up being placed next to each other (Figure 54), intuitively, because they belong to the same cluster, which also breaks the model. In general, it is not the case that all connected nodes are close or that all disconnected nodes are distant.

Certain networks, e.g., lattices, can be spatialized so that each node is close only to its neighbors. However, for most networks, such a layout is impossible. For instance, the arms of a star-shaped network (e.g., Figure 55) cannot be well separated while also being close to the central node. There is simply not enough space in a Euclidean space of two dimensions. This would work in a hyperbolic space or in many more dimensions but, then, we could not represent it effectively.

In a non-star network, the hubs create the same problem. More generally, the extremely skewed degree distribution of complex networks strongly mismatches

Figure 54. A zoom on the network map of our preliminary example (Figure 5). Arrows highlight disconnected nodes placed next to each other. If you look closely, you can find many more.



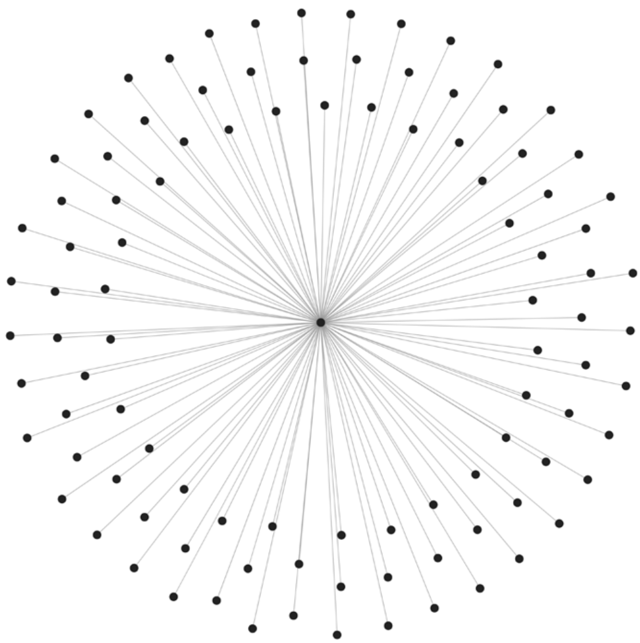


Figure 55. A star-shaped network. Layout: Force Atlas 2, default settings. The peripheral nodes cannot be well separated while also being close to the central node. The higher the number of peripheral arms, the stronger this effect.

this interpretive model. However, as we have seen, prior to the complex network turn, many test networks (polygons, lattices) had a homogeneous degree distribution. I think that "close means connected" was reasonably true for diagrams but categorically wrong for complex networks, notably because of their hubs.

Now, you may be thinking, "in a star, the peripheral nodes are still indirectly connected and that this is a valid reason to have them close. Couldn't visual distance reflect being directly *or indirectly* connected?" The next model formalizes this intuition.

MODEL 2: THE VISUAL DISTANCE REPRESENTS THE GEODESIC DISTANCE

The geodesic distance is the length of the shortest path between two nodes. In short, how many successive links stand between them. In the star of Figure 55, all nodes are at a geodesic distance of 1 or 2, so it makes sense that they are relatively close. However, other counterexamples show where the model breaks. In the case of a clique, where every node is connected to every other node (Figure 56(a)), the geodesic distance between all the node pairs is exactly 1, yet the distances vary. Arguably, this is a special case, so let us look at a random network (Figure 56(b)). Here, we have 100 nodes, where each pair has a 50% chance of being connected (the network is half as dense as a clique). It turns out that any two nodes are at a geodesic distance of 1 or 2, never more. In a dense network, the geodesic distances are short. The hubs of complex networks also make the problem worse by creating topological shortcuts. Intuitively, the geodesic distance is too imprecise because it can only take a very limited set of values (small natural numbers, e.g., 1, 2, 3). Short geodesic distances are a characteristic feature of complex networks, the famous "small-world phenomenon" (Watts and Strogatz, 1998).

In "What Do We See When We Look at Networks?"* we compared the geodesic distance of our example network to the Euclidean distance in our force-directed layout (Figure 57). Although we observed a tendency of proportionality (the slope of the dots), the variance was so important (large error bars) that, ultimately, the correlation was poor ($R^2 = 0.167$). The chart says, for instance, that for the 10% closest pairs, the geodesic distance probably ranges from 2 to 4, while for the 10% most distant pairs, it probably ranges from 3 to 5, which is not very informative. The visual distance may represent the geodesic distance but only as a general tendency. As a model, it does not provide local predictions because of this high variance. It tells us something about many pairs of nodes at once but nothing

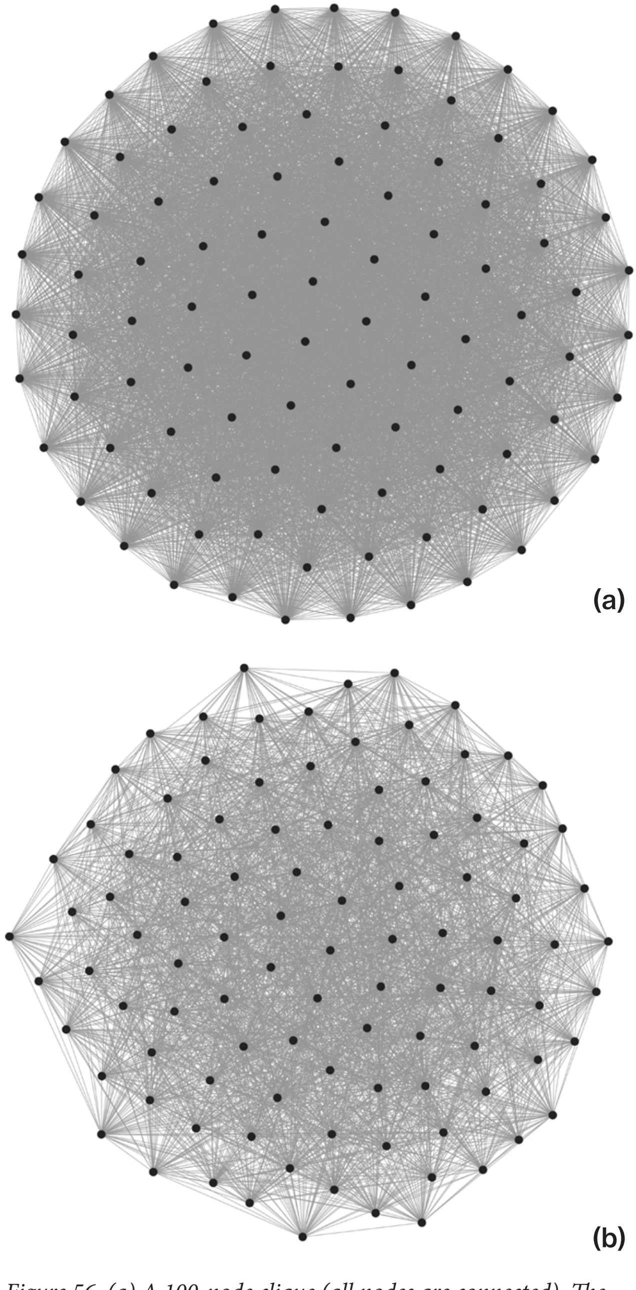


Figure 56. (a) A 100-node clique (all nodes are connected). The geodesic distances all equal 1. (b) A 100-node random network where two nodes have a 50% chance of being connected. The geodesic distances equal 1 or 2. Layout: Force Atlas 2, default settings.

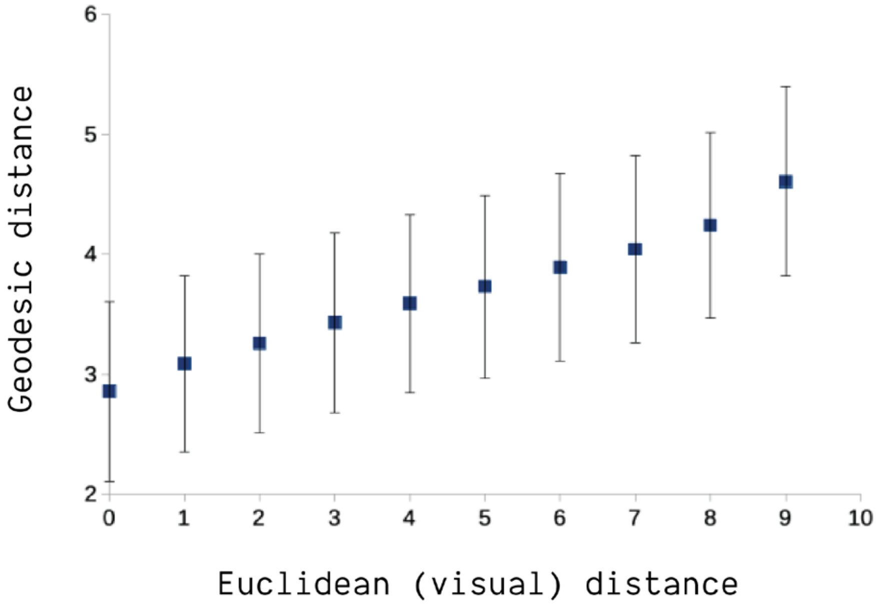


*Figure 57. The plot represents the mean and standard deviation as error bars (of the geodesic distance for the binned Euclidean distances "i" (i = int(distance/distance_max)). Correlation: $R^2 = 0.167$. Network from "What Do We See When We Look at Networks?"**

about a given pair of nodes in isolation. It is not sufficiently accurate to provide a useful interpretation.

Of course, this plot only speaks for one case, but it illustrates the problem. The geodesic distance takes too few different values, preventing it from correlating closely with the Euclidean distance, which is continuous. Nonetheless, averaged on many different pairs, it seems that there is a tendency of correlation. If the intuition of the geodesic is valid but not sufficiently nuanced, then could a statistical variant make it? The next model formalizes this.

MODEL 3: THE VISUAL DISTANCE REPRESENTS THE MEAN COMMUTING TIME

The *mean commuting time* is the average number of steps that a random walker, starting from one node, takes to reach the other and then return to the starting node (Fouss et al., 2007). Intuitively, it relates to the geodesic distance, though more nuanced, as it can take non-integer values. It also takes more context into account. We tested this in "What Do We See When We Look at Networks?"* (Figure 58), and it turned out much worse than the geodesic distance, i.e., with

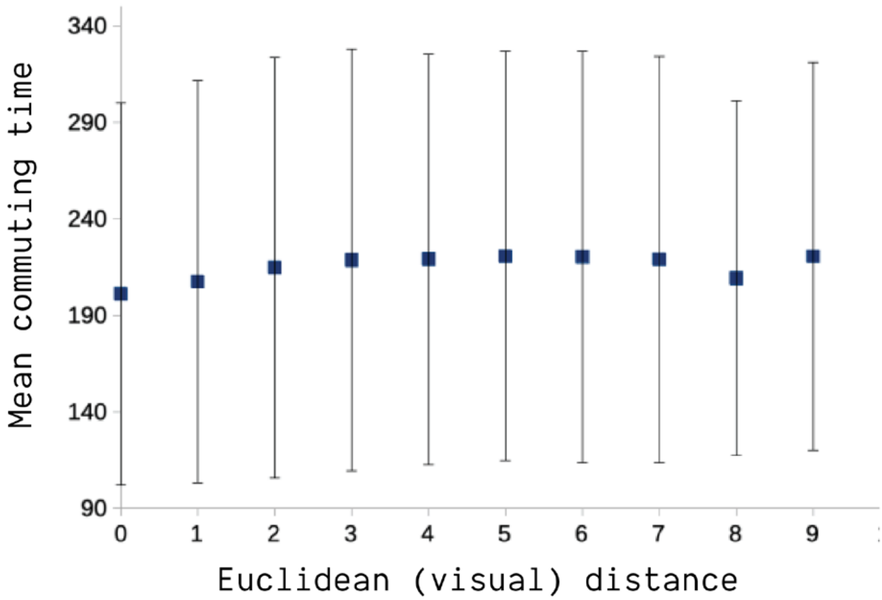


*Figure 58. The plot represents the mean and standard deviation as error bars (of the mean commuting time for the binned Euclidean distances "i" (i = int(distance/distance_max)). Correlation: $R^2 = 0.0025$. Network from "What Do We See When We Look at Networks?"**

no correlation ($R^2 = 0.0025$). Indeed, random walkers can drift considerably far away from even a neighboring node, especially in the presence of hubs. This model is categorically wrong, despite the intuition.

MODEL 4: NODES ARE CLOSE IF, AND ONLY IF, THEY ARE IN THE SAME CLUSTER

This model is invalid for reasons that are completely different from those of the above models. Although it might be true, but the formulation is wrong. In short, "nodes are close when they are in the same cluster" is either tautological or meaningless. We know, from Noack's work (2009), that clusters (in the sense of modularity) and node proximities result from the same process. So on one hand, yes, visual clusters and topological clusters are basically the same thing. On the other hand, this characterization is tautological. We know of modularity clusters no less and no more than we know of visual clusters (Figure 59). Concretely, this interpretive model boils down to "two nodes get close from an energy model if, and only if, they get close from an energy model."

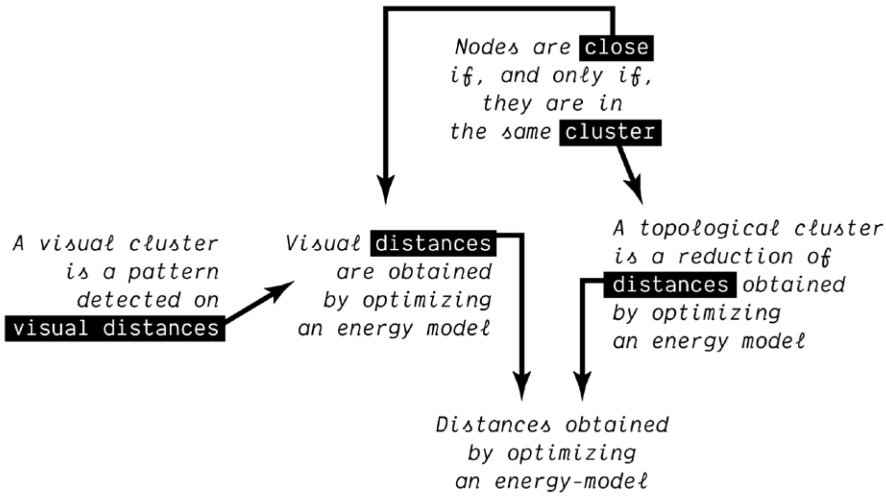


Figure 59. The regress of visual clustering.

Let us call the tautological meaning of this model a *regress* with reference to the "experimenter's regress" (Collins, 1981). If visual clusters are modularity clusters and vice-versa, then what are those clusters? The problem with this regress, and of this model, is that it only articulates with the topological structure on a superficial level. I have argued in this chapter why the LinLog does not explain what we see in networks: we do not know precisely why the optimization of energy models provides cluster separation. We do not have much doubt about the fact itself, but we cannot retrace its cause with enough accuracy to pinpoint the right topological structure. Both the visual and topological clusters emerge from the energy model. We cannot explain why two nodes end up in the same cluster, visually or topologically, without running the calculations. In the remainder of this chapter, I argue that, when it comes to visual patterns, there is a fundamental problem with the notion of clusters.

CLUSTERING BEYOND CLUSTERS: NON-PARTITION COMMUNITY STRUCTURE

Here, I expand an argument from "What Do We See When We Look at Networks?"* on the nature of clustering. I draw arguments and visual examples from the literature on graph partitioning to explain why community structure cannot be reduced to a matter of mutually exclusive groups.

Labatut and Orman (2017: 1) propose a review of the characterization of community structures in networks: "Community detection is one of the most studied problems in the domain of Network Science. … Yet, almost all works in the field of community detection concern the definition of detection tools, and the evaluation of their precision or speed. Very few researchers have addressed the problem of characterizing and interpreting the communities." They note an important distinction between "topology only" methods and approaches "taking advantage of nodal attributes." When it comes to visualizing links, we understand communities as purely topological (not a normative statement, but a pragmatic one). For Labatut and Orman (2017), like Fortunato (2010) in his review of community detection algorithms, communities are exclusive groups of nodes—partitions. Each node belongs to one group—and exactly one. This formulation of the problem has practical upsides, but it does not match intuition as well as one would hope. According to Fortunato (2010: 82): "The problem of graph clustering, intuitive at first sight, is actually not well defined. The main elements of the problem themselves, i.e. the concepts of community and partition, are not rigorously defined, and require some degree of arbitrariness and/or common sense. Indeed, some ambiguities are hidden and there are often many equally legitimate ways of resolving them." There is a fundamental limitation to conceptualizing community structure as a graph partition.

A first problem with the intuitive notion of the group (or community) are the different meanings ascribed to it in different contexts. Not only has sociology its own debate on the notion (Freeman, 1992), graph theory also faces multiple characterizations. Two well-known and mutually exclusive notions are the group as more-densely-connected nodes (e.g., modularity) and the group as a set of nodes with consistent links to other groups (e.g., the stochastic block model [SBM]). SBM seems more general at first glance because it allows a group (or block) to be less connected internally than externally. Unfortunately, it leads to inconsistency effects that do not exist for dense groups. As Peixoto (2019) shows, a similar network may be correctly defined by multiple incompatible SBM structures simultaneously. He provides an example (Figure 60) where the same network can be equally reduced to a core–periphery structure or a two-communities structure. Both standpoints are equally valid. Clusters defined as densely connected groups are not subject to such massive delineation inconsistencies, but in their own way, they face the same problem.

Yang and Leskovec (2014) developed a model of structural communities as overlapping tiles. Their main example (Figure 61) shows "a Facebook friendship network of a particular user … with communities explicitly labeled by the user"

(p. 1896). They show that partition-based community detection methods do not provide a satisfying reduction of this structure. Indeed, as our intuition tells, people belong to multiple social circles at once, and communities are not necessarily exclusive. As Yang and Leskovec observe, the "overlapping" area, which is denser than each individual "tile," tends to defeat community detection algorithms because it creates a strong core–periphery structure in a way that is reminiscent of the SBM behavior highlighted by Peixoto (Figure 60).

Peixoto (2020) also shows "that it is in general not possible to obtain a consistent answer" to the question of community partitioning "when the underlying distribution is too heterogeneous" (p. 1). In short, for some networks, there are different, equally valid partitions, a point that echoes his earlier observations (Peixoto, 2019). Figure 62 illustrates "the pitfalls of consensus estimation in community detection" (Peixoto, 2020: 2), where distinct partitionings of the network coexist. Each node is represented as a pie chart of its probability of belonging to different clusters. The figure shows poles in the sense I proposed in my Gestalt model: clusters are well defined on the sides and ambiguous in the middle.

In the literature, this coexistence of multiple well-defined partitions is known as a *degeneracy* problem. According to Calatayud et al. (2019), for some empirical networks, the "solution landscape" of community detection "is degenerate" because "small changes in an algorithm parameter or a network due to noise can drastically change the best solution" (p. 1). Peixoto (2020) also points to the "inherent degeneracy" of community detection. Good et al. (2010) were able to explore experimentally and visualize this degeneracy (Figure 63) by focusing on the modularity function's structure in the vicinity of the degenerate high-modularity partitions. Their assessment of the situation is unambiguous. First, "[t]he optimal partition may not coincide with the most intuitive partition" (p. 11). Second, "[t]here are typically an exponential number of structurally diverse alternative partitions with modularities very close to the optimum (the degeneracy problem). This problem is most severe when applied to networks with modular structure" (p. 11).

The language of mathematics is not so helpful, here. Peixoto (2019, 2020), for instance, repeatedly states that the purpose of community detection is to "extract" a structure. This suggests that the structure predates its detection, which is misleading (more on this shortly). The term "detection" is similarly evocative, but I concede that it is so overused that its meaning has been diluted. The term

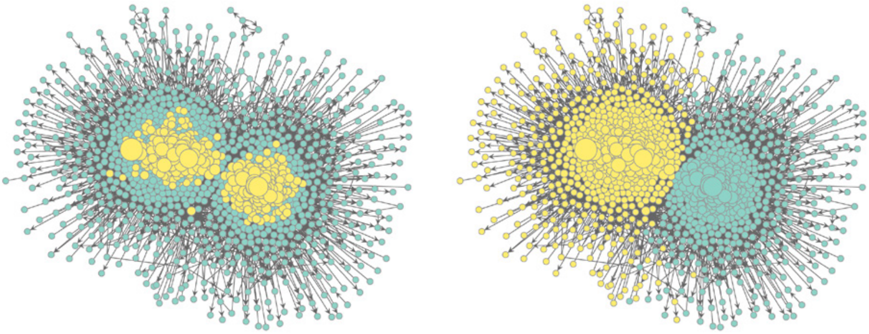


Figure 60. The same network with two different, equally valid partitions: center–periphery or density clusters (Peixoto, 2017: Figure 7), licensed under CC-BY-SA.

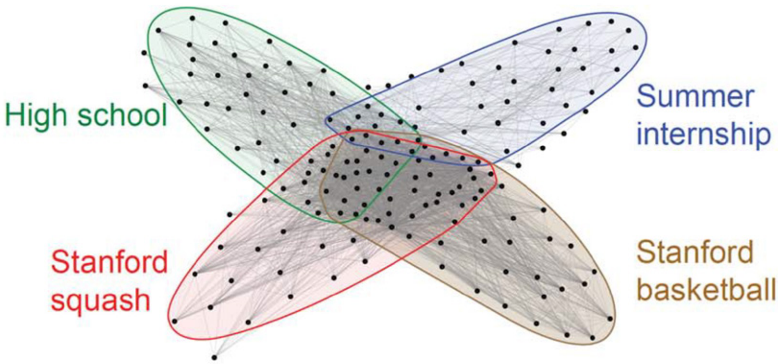


Figure 61. Overlapping communities (Yang and Leskovec, 2014: Figure 6). © 2014 IEEE.

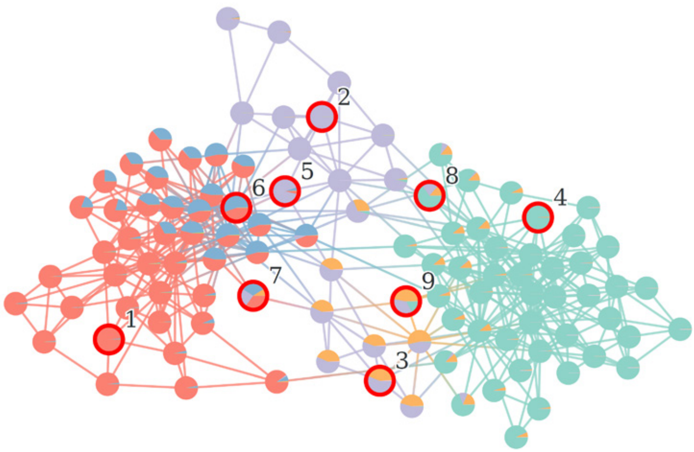


Figure 62. This network has no single optimal answer to community detection. Certain nodes have split probabilities of belonging to different partitions (Peixoto, 2020: Figure 4). Licensed under CC-BY-SA.

"degeneracy" might suggest that the community structure is somehow broken or that it is not real. This is seemingly confirmed by the fact that the partition problem has no proper solution, but this would be a misunderstanding. We have very reliable ways of determining that a network has a modular structure. For instance, we could run a community detection algorithm and just look at the resulting modularity, which would measure how separated the resulting clusters are. In Figure 63, we would find a solution somewhere at the top of the plateau, and in this case, we would find a modularity of about 0.8, which would determine a modular structure. The optimal solutions are indeed numerous and varied, but they all have a high modularity. This high modularity, and therefore any near-optimal partition found, unambiguously tells us that the network has a modular structure. The ambiguity is not about the modularity of the structure but about the division of the modules. The "degeneracy problem" specifically points to the fact that a modular structure does not necessarily break down into clear-cut clusters, even when it is unambiguously modular. Yang and Leskovec's (2014) "overlapping tiles" and Peixoto's (2020) modeling of "mixed populations of partitions where multiple consensuses can coexist" address this issue from different angles.

I have documented such a situation in a previous paper, co-authored with Dominique Boullier and Maxime Crepel (Boullier et al., 2016). Their qualitative exploration of the web of French literature (I only contributed to network analysis) featured an interesting network of websites and hyperlinks on comics and children's books (Figure 64). Depending on the node attributes mapped, two distinct cuts appeared: vertical on the first topic (literary genre) and horizontal on the second one (type of actor). This example is empirical and manually coded (the categories are the ground truth, in the language of statistics). It is not fabricated to showcase the possibility of degenerate modularity clustering. The empirical categories show that two mutually exclusive cuts naturally coexisted in this network. This case is reminiscent of the overlapping tiles of Yang and Leskovec (2014), but the way in which the clusters were combined was different.

THE RHETORIC OF STRUCTURE EXTRACTION

I argue that the community structure does not necessarily look like clear-cut clusters. Is this subversive? I do not think that the idea is particularly novel, but it certainly conflicts with established discursive norms, in particular the argument that the community structure needs to be *extracted*. The rhetoric of structure extraction is widespread in the computer science literature, and I only provide here

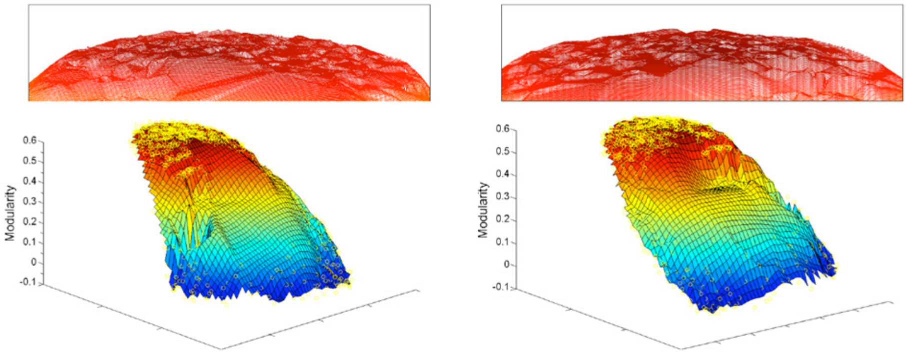


Figure 63. The degenerate landscape of community detection: optimal solutions (on top) for a plateau of multiple different, equivalently good partitions (Good et al., 2010: Figure 13). Reprinted figure with permission from Benjamin H. Good, Yves-Alexandre de Montjoye, and Aaron Clauset, Physical Review E, 81(4), 2010. Copyright 2010 by the American Physical Society.

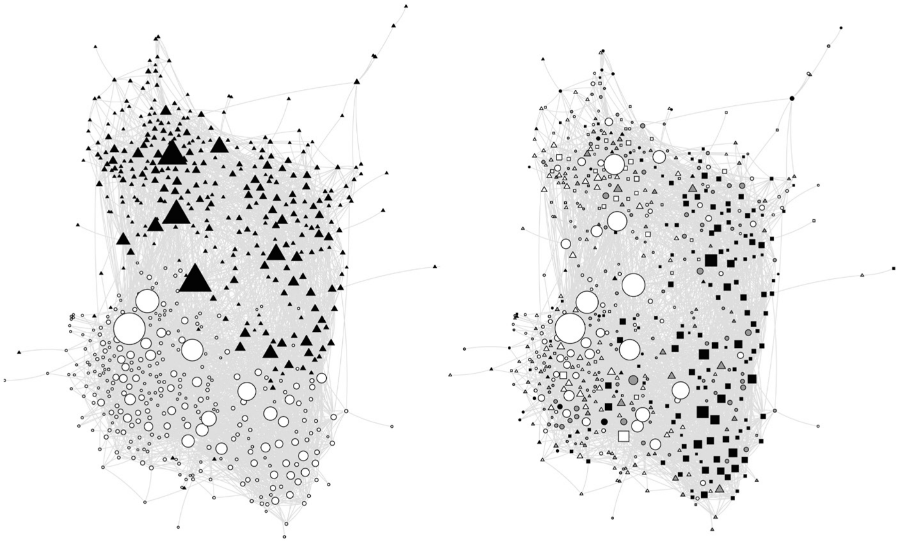


Figure 64. A network of websites about comics and children's books, same layout (Force Atlas 2) with two mapped node attributes (Boullier et al., 2016: 25, Figure 8). On the left, literary genre. On the right, type of actor. The two apparent divides, horizontal on the left and vertical on the right, are equally valid.

an illustration focused on the question of clusters. Leskovec et al. (2010) propose an "empirical comparison of algorithms for network community detection," considered a reference.[18] In the following quotes, I highlight the terms related to extraction. They define community detection as an application of "approximation algorithms or heuristics to **extract sets of nodes**" (p. 1). "Once **extracted**, such clusters of nodes are often interpreted as organizational units in social networks" (p. 1.). "Next we consider … algorithms and compare their performance in **extracting clusters** of various sizes" (p. 5). "Graclus seems to **find clusters of ten or more nodes**, while Newmans's algorithm also **extracts very small pieces**" (p. 5). "[W]e **extracted clusters** based on their conductance" (p. 7). "[G]raph partitioning algorithms … do **a good job of extracting clusters** at all size scales" (p. 9). In addition, the expression "**extracted clusters**" is stated three times. Importantly, Leskovec et al. are not the only ones referring to clusters and community structure as the product of an extraction (see, e.g., Blondel et al., 2008; Correa and Ma, 2011; Fortunato, 2010; Vehlow et al., 2015).

The term "extraction" has multiple meanings, such as "computation" or "measurement", but it is not always problematic. The rhetoric of structure extraction I point to refers specifically to the implicit idea that the said structure predates its extraction. This assumption is especially problematic when it comes to clusters. A proper use of the term can be found, for instance, in the work of Newman and Girvan (2004) on community detection. Their approach determines clusters beforehand, before an algorithm tries to retrieve ("extract") them: "as a controlled test of how well our algorithms perform, we have generated networks with known community structure, to see if the algorithms can **recognize and extract this structure**" (Newman and Girvan, 2004: 8, emphasis added). In this case, the preexistence of clusters is not an assumption; it is a methodological statement. It defines the game that their algorithm tries to be good at. This paper predates the other uses of the rhetoric mentioned above, and it might be one of its points of origins (when it comes to community structure). Unfortunately, the rhetoric takes on a substantially different meaning when the clusters are assumed instead of implemented. The discourse becomes realist: it frames community structure as a reality independent of its extraction. It loses the constructionist nuance of Newman and Girvan's work. If we "wash away the assumption that there is a reality out there beyond practice that is independent, definite, singular, coherent, and prior to that practice" (Law, 2010: 12), then the performativity of computer science papers and algorithms becomes visible.

18 Google Scholar reports over 1,000 citations (Accessed 05 November 2020).

The problem with the realist understanding of community structure is the self-referential statement it leads to. Indeed, community structure is *performed* by community detection algorithms. We know that a community structure exists because we can obtain it from an algorithm. Before the algorithm, we cannot tell for sure whether the community structure is present. For instance, a community structure can be defined as the existence of a high-modularity partition. We can then run a modularity-clustering algorithm (e.g., Newman and Girvan, 2004; Blondel et al., 2008), which would output a partition. We can then measure the modularity of the partition, and if it is high, we say that the network has a community structure. This is a regress because, in order to measure the degree of community structure of a network, we have to cut the same network into separated communities. The community structure does not predate its measurement; it is performed by it. This is contrary to the realist interpretation, which leads to tautological statements. Indeed, in a realist setting, evaluating a community detection algorithm requires comparing the output to the input. However, in practice, the input is defined as whatever produces a good output. This means that the trial cannot fail: community detection algorithms always successfully extract communities because when they do not, they perform the absence of a community structure. The realist interpretation of community structure extraction does not support a proper evaluation of clustering algorithms.

This may be the philosophy of science; the argument is not an arbitrary speculation. The rhetoric of cluster extraction has obfuscated a very important idea. Clustering does not only come in the shape of partitions. In fact, it is pretty obvious that clear-cut clusters are rare in empirical networks. Partitions are reductions of the community structure; they dismiss information to the benefit of computability. Partitions are very convenient, which I do not deny! Nonetheless, by assuming that the community structure exists as hidden partitions, we are blinded to certain kinds of community structure: locally clustered but not sufficiently dense to be unambiguously reduced to clear-cut clusters—which I call "stretchings."

STRETCHINGS

I call stretching a topological structure that looks like a group because it is locally dense everywhere, though not necessarily compact—a stretched cluster, if you will. Intuitively, it englobes all kinds of odd-shaped but locally dense structures (Figure 65). By "locally dense everywhere," I mean that the clustering coefficient of all nodes is high: the friends of anyone's friends tend to be their friends, hence the community feature. This probability may vary depending on the nodes, though. By "compact," I mean that this structure does not necessarily have a very short diameter or short average length path, hence the variety of possible shapes.

I use this idea of a stretch to convey the idea of extension, of non-compactness, but I acknowledge that it might be misleading: stretchings might not look stretched. Extensiveness suffices. The term resonates with my experience, though, because of the "poles" highlighted earlier in this chapter that appear to stretch the rest of the network. Of course, this way of seeing things is typically that of a human relying on a layout. The notion of shape, in a purely topological context, does not make much sense. Us puny humans have a hard time comprehending non-Euclidean spaces.

My motivation to name such an indefinite array of topologies is simply to reclaim them as *community structures*. Stretchings are community-like everywhere, yet we cannot reduce them to a cluster because they are extensive, and we cannot cut them into well-separated parts. No cut would provide a good separation because stretchings are locally dense everywhere. If this sounds abstract or contradictory, I hope a practical example will make it clear. The approach I propose here is only one of many possible ways to do it, but it suffices to illustrate the key properties of stretchings. In this model, we simply chain cliques very tightly (Figure 66). We start by setting a clique size (here, 5) and creating the first clique (all nodes are connected). Let us call this clique the *tip* clique. At each iteration, we remove the oldest node in the tip clique and add a new one that we connect to all the other nodes of the tip clique. This gives us a new tip clique that differs from the previous one by just one node. We keep doing this until we want to stop.

Figure 67 shows a chained-clique network of 199 nodes generated with a clique size of 100. It is elongated, as expected, but this is not the effect of the less dense area in the middle. By design, it is locally very dense everywhere, with an average clustering coefficient of 88% and a density of 75%. By comparison is my test network about Europe on *Wikipedia* (Figure 5), which has a clear community structure, about the same number of nodes, but only an average clustering coefficient of 43%. In some sense, this stretching looks like a single cluster, although an oddly shaped one. We cannot divide it into well-separated subclusters. Modularity clustering cuts it in the middle, as intuition suggests, but the resulting modularity is very low: 0.164 (versus, e.g., 0.780 for *Wikipedia*-Europe). Let us see what happens if we make a longer chain of cliques.

Figure 65. A metaphor for stretchings: stretched clusters.

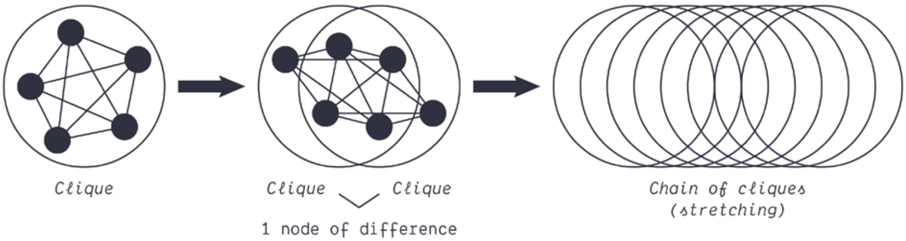
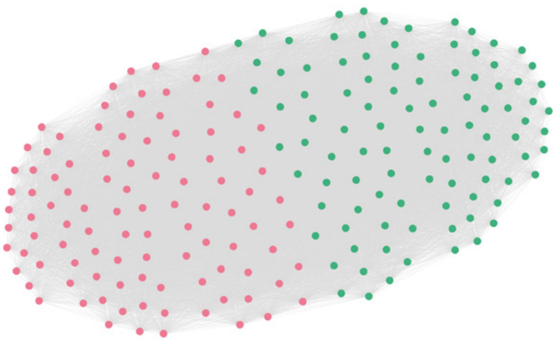


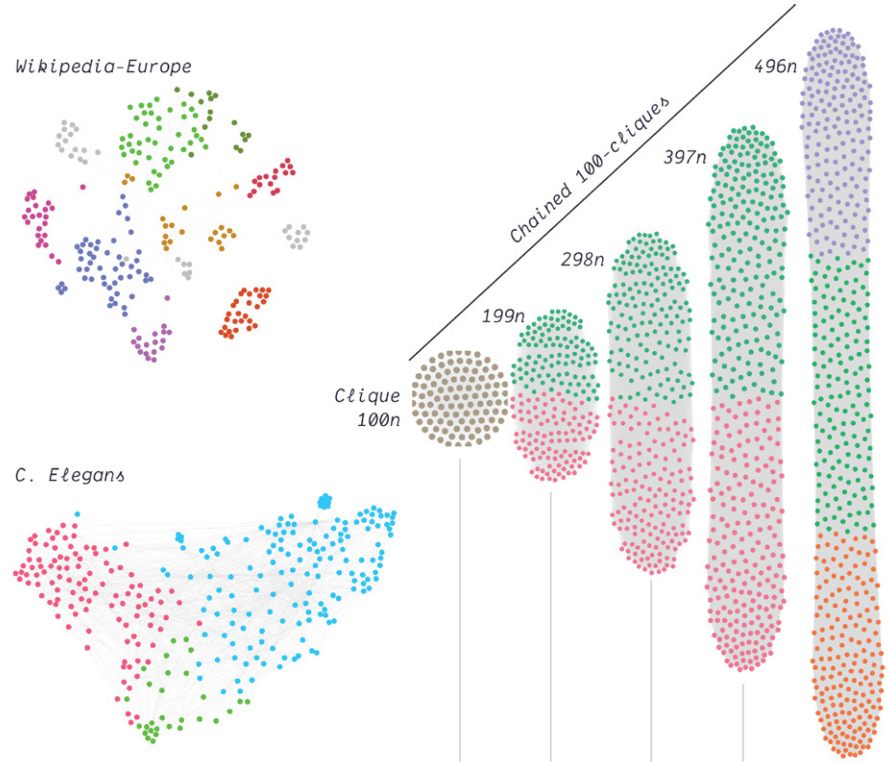
Figure 66. The chained-clique model produces stretching networks.

Figure 67. A network of 199 nodes, 14,751 edges, generated by a chained-clique model with a clique size of 100. Layout: Force Atlas 2, default settings. Diameter: 2. Average clustering coefficient: 0.884. Density: 0.749. The colors correspond to a clustering found by the Louvain algorithm (Blondel et al., 2008), with a resulting modularity of 0.164.



Let us set the clique size to 100. A 100-node chained clique is a single clique of 100 nodes with a diameter of 1. If we stack one more clique, the diameter becomes 2, as a 2-path now exists. We can stack up to 99 additional cliques and keep a diameter of 2, but the 100th will set the diameter to 3. So the biggest chained clique of diameter 2 has 199 nodes, that of diameter 3 has 298 nodes, and so on. I generate the biggest chained cliques of diameters 1 to 5 and compare them to two networks we have already seen: *Wikipedia*-Europe and C. Elegans. I visualize these networks and various metrics in Figure 68. The chained cliques appear stretched under the action of the layout (Force Atlas 2, default settings), which is the expected effect of the attraction–repulsion energy model. We also see that the longer the chain, the more divisible it becomes, as intuition tells. In the 496-node chained clique, the modularity clustering algorithm (Blondel et al., 2008) finds three clusters, and the two opposite clusters have no links. However, the modularity is not that high (0.442), and the average clustering coefficient remains very high (0.802). The chart at the bottom of Figure 68 shows that even though the modularity rises as the chains get longer, it remains low—lower, for instance, than *Wikipedia*-Europe. Therefore, it resists partitioning. Similarly, the average clustering coefficient drops as the chain gets longer, but it remains characteristically high, much above *Wikipedia*-Europe and C. Elegans. It is locally dense. Like our intuition of a cluster, it resists partitioning and is locally dense. However, unlike a cluster, it is extensive: the average path length can significantly surpass 1 (the minimum, in the case of a clique) as the chain gets longer. A chained 100-clique of 5,000 nodes has an average path length of 17 (*very* extensive, and the diameter is 51!) while remaining cluster-like, with an average clustering coefficient of 0.752 (high), and its characterization as a community structure via modularity is good but not great (modularity of 0.646, between C. Elegans and *Wikipedia*-Europe). To sum up, chained cliques are locally cluster-like, but unlike clusters, they are extensive. As their modularity is low for any partition, they would not be considered community structures.

The chained-clique model produces a one-dimensional extension, but with the same approach, we could generate plane-like, volume-like… anything-like structures that are locally dense everywhere, extensive, and resistant to partitioning. These are instances of stretchings: locally dense but extensive. I reclaim the right to call these topological arrangements "community structures," despite their non-separability, on the motive that they are locally community-like (dense) and have a distinctive structure (extension). Stretchings are the community structures missed by the ordeal of partitioning. I hypothesize that force-driven layouts



Network	Wikipedia-Europe (undirected)	C. Elegans (undirected)	100-clique	Chained 100-cliques 199 nodes	Chained 100-cliques 298 nodes	Chained 100-cliques 397 nodes	Chained 100-cliques 496 nodes
Nodes	249	297	100	199	298	397	496
Edges	631	2345	4950	14751	24552	34353	44154
Diameter	6	5	1	2	3	4	5
Average path length	4.085	2.456	1	1.125	1.557	1.877	2.202
Density	0.017	0.049	1	0.749	0.555	0.437	0.36
Average clustering coefficient	0.43	0.308	1	0.884	0.838	0.815	0.802
Modularity	0.78	0.346	0	0.164	0.298	0.356	0.442
Number of clusters	10	3	1	2	2	2	3

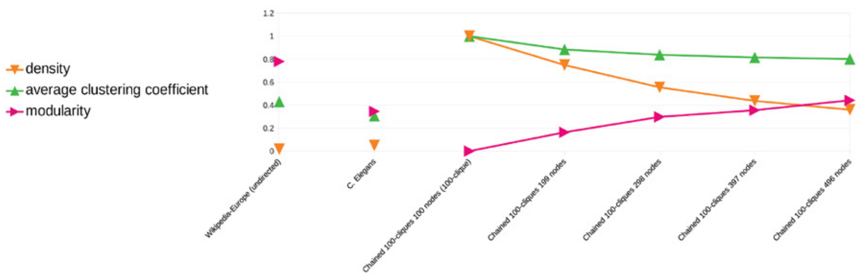


Figure 68. Two empirical networks, Wikipedia-Europe and C. Elegans, compared to chained 100-cliques of different sizes. The modularity of the chained cliques is lower than that of the empirical networks, while the density and average clustering coefficient are higher.

mediate well the community structure of stretchings, but it was not identified because layout quality was conceptualized as a matter of partitioning. When I look at Figure 68, I find C. Elegans more stretching-like than *Wikipedia*-Europe, and I find that despite its poor modularity, its structure is well manifested by a force-driven layout: the nodes on the sides tend to be connected to those around them, while those in the middle tend to be connected to multiple sides and the middle. This is just an intuition, of course, as testing this hypothesis would require a quantification of the layout quality. In the next chapter, I engage with this question from a practical angle.

5. INTERVENTIONS

In this chapter, I propose two interventions in the field of network visualization. Each contribution tinkers with practices in a different way. I did not offer a normative take on VNA in this dissertation, and I do not intend to. The instruments of network analysis have their own lives and subcultures, and I have sufficiently accounted for these factors in this dissertation. Nonetheless, I have expressed my disagreements with the practices and the literature, which can be tinkered into a productive engagement with network practices. My first tinkering proposes a drawing of a scale on network maps that gives a clear relation between distances and links when possible. My second tinkering seeks a formulation of the notion of community structure that is simple enough to state in a sentence in plain English and accurate enough to predict the visual distances in a force-directed layout.

TINKERING 1: A VISUAL QUANTIFICATION OF DISTANCES IN NETWORK LAYOUTS

Here, I aim to provide a contextual statement about a given network map where nodes have been placed by a force-directed algorithm (or similar). I present the process in detail in "Connected-Closeness,"* which aims to quantify the intuition that *most connected nodes are very close*. It does so by defining the distance (Δ_{max}) that best captures this notion (Figure 69).

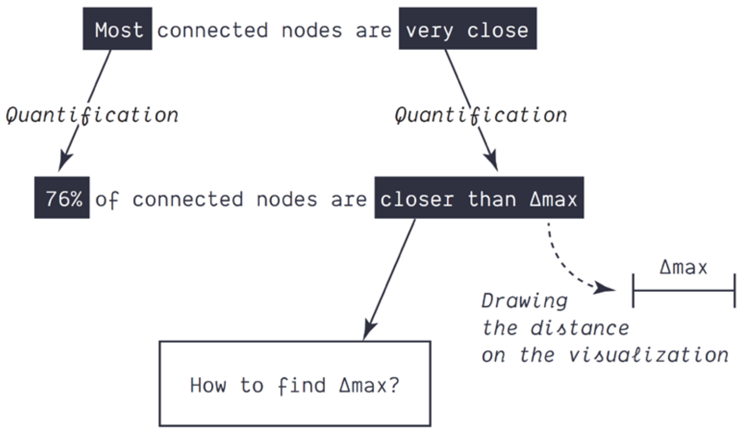


Figure 69. A quantification of an intuitive statement about distances on a network map.

Finding a meaningful Δ_{max} is not straightforward. Indeed, given a long-enough distance, all connected nodes are close enough (Figure 70). Δ_{max} is not about capturing the most connected pairs; it is really about capturing more connected pairs *than one would anyway*. The notion of connected-closeness formalizes this intuition: it looks at how many edges are shorter than a given distance but discounts the expected number of edges that would be shorter if all edges were *rewired* at random.

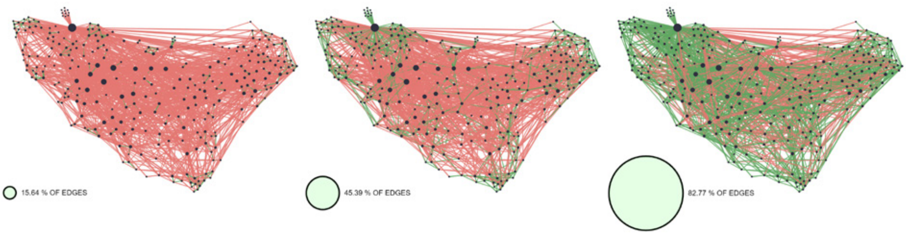


Figure 70. Network: C. Elegans. Layout: LinLog (Force Atlas 2 implementation). A given part of edges is smaller than a given selection distance. The diameter of the circle represents the selection distance. Shorter edges are in green, longer edges in red.

Formally, connected-closeness is defined as a metric $C(\Delta)$, a function of the Euclidean distance Δ on the network map, that tells how many edges are shorter than Δ *compared to expectations* (i.e., the same layout but with edges rewired at random). This metric is null for $\Delta = 0$ (we expect to capture no edges and do not capture any) as well as for Δ larger than the whole network (we expect to capture all edges, and do so). In between, $C(\Delta)$ rises and falls (edge cases aside). It reaches a maximum $C_{max} = C(\Delta_{max})$ where the distance Δ_{max} captures the *most unexpected edges*. "Connected-closeness"* defines the metric precisely (see also Figure 71).

The maximal connected-closeness distance Δ_{max} can be drawn on the network visualization, for instance, as a grid, and be used to build a simple contextual statement such as "76% of connected nodes are Δ_{max} or closer" (see Figures 5 and 72). However, this statement does not account for the specificity of Δ_{max}. It does not tell that Δ_{max} captures more edges *than expected*. For this reason, I propose a visualization of the number of captured edges compared to the *expected* number. This information is visualized as the pie chart at the bottom of the visualization (Figures 5 and 72). The maximal connected-closeness C_{max} is represented by the blue slice of the pie chart.

Important quantities

$C(\Delta)$ is the **connected-closeness** for the Euclidean distance Δ.
It is defined as the **percentage of unexpectedly close connected nodes**, where close means closer than Δ (see below).

Δ_{max} is the **distance of maximal connected-closeness**.

$C_{max} = C(\Delta_{max})$ is the **maximal connected-closeness**.

Definition of connected-closeness

$$C(\Delta) = \frac{E(\Delta) - E_{expected}(\Delta)}{E(\infty)} = \frac{E(\Delta)}{E(\infty)} - \frac{p(\Delta)}{p(\infty)}$$

- $E(\Delta)$ is the count of edges shorter than the Euclidean distance Δ
- $E(\infty) = e$ is the total count of edges (i.e. the graph size e)
- $E_{expected}(\Delta) = E(\infty) \times \dfrac{p(\Delta)}{p(\infty)}$ is the count of *expected* edges shorter than Euclidean distance Δ
- $p(\Delta)$ is the count of node pairs closer than the Euclidean distance Δ
- $p(\infty) = n \times (n-1)$ is the total count of node pairs (n is graph order)

Definition of the maximal connected-closeness

C_{max} is defined as the maximum of $C(\Delta)$ for any Δ

Δ_{max} is the Euclidean distance where $C(\Delta)$ is maximal. In case of ties, the smallest Δ is retained.

Figure 71. Mathematical formalization of connected-closeness.

Note that Δ_{max} is only relevant insofar as C_{max} is sufficiently high. Indeed, if Δ_{max} is close to zero, it means that no distance in particular captures more edges than expected. In that case, as a protection against misinterpretation, I propose to declare Δ_{max} *non-applicable* and to not visualize it, even though, technically, it could be calculated.

Also note that Δ_{max} does *not* mean that closer nodes have a good chance of being connected. It only works the other way around: connected pairs have a good chance of being closer. To guard against this misinterpretation, I suggest featuring this information (it is the last line below the pie chart in Figures 5 and 72). In the case of C. Elegans, even though Δ_{max} captures 76% of connected pairs, if we randomly pick a node pair closer than Δ_{max}, we have only a 9% chance of it being connected.

As a complement, Figure 73 shows connected-closeness for a stretching rendered by Force-Atlas 2. Δ_{max} captures 94% of the edges, more than the 92% of *Wikipedia*-Europe (Figure 5). C_{max} cannot be as high, as the stretching is much denser. The remarkably high C_{max} shows that the node placement reflects the extension of the stretching.

Connected-closeness is a remarkably consistent metric that captures many interesting aspects of node placement strategies based on edge-length minimization. It is consistently high for force-directed algorithms and consistently low for random layouts. It accounts for the fact that force-directed layouts are more efficient on sparse networks than on dense networks. Furthermore, as the community structure decreases, so does the maximal connected-closeness. The paper "Connected-Closeness"* features a benchmark that characterizes and visualizes these different points, which I do not reproduce here. Beyond helping us understand network maps, connected-closeness can also act as a layout quality metric. It offers multiple benefits:

1. It allows the formulation of a quantitative statement about the placement of nodes in the visualization. A simple statement such as "76% of connected nodes are Δ_{max} or closer" provides contextual information on the relation between the topology (connectedness) and its representation (closeness).

2. The maximal connected-closeness C_{max} assesses the validity of the layout. Different layouts have different goals, and this metric only accounts for one of them (bringing connected nodes closer). It is not the only way to validate a layout, but it is one. It states a game at which the layout is supposedly good and checks that it actually is. The benchmark presented in "Connected-Closeness"* shows that force-directed layouts are indeed good at the game of bringing connected nodes closer, but C_{max} also detects situations and layouts that are bad at it. It is also remarkably consistent.

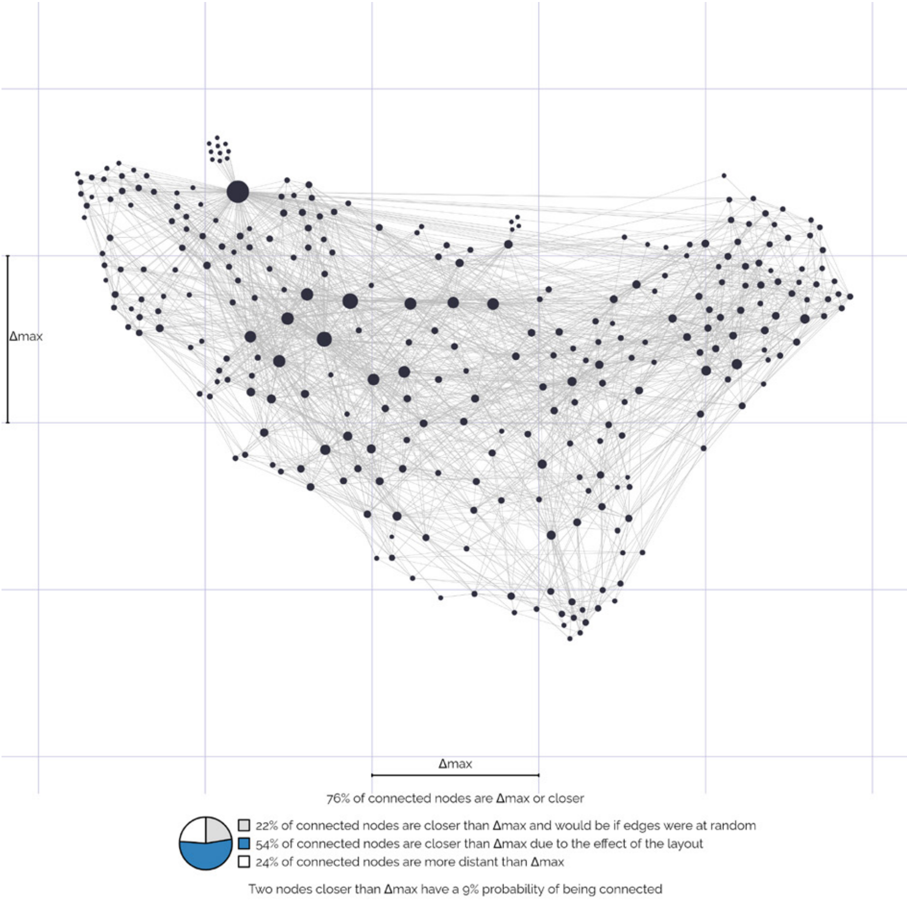


Figure 72. C. Elegans (Layout: LinLog) visualized using Δ_{max} as a grid.

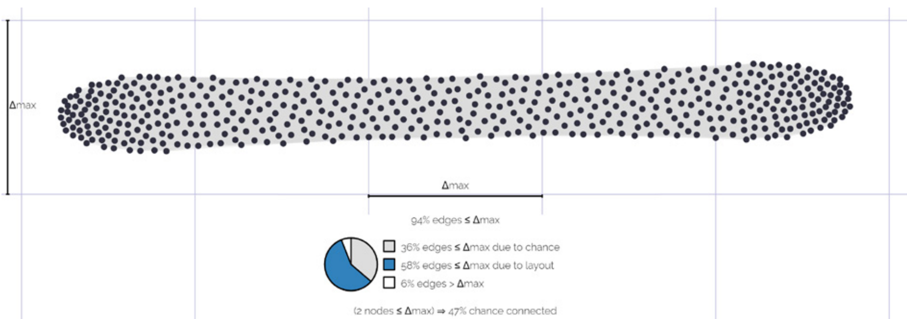


Figure 73. A chained 100-clique of 496 nodes (Layout: Force Atlas 2) visualized using Δ_{max} as a grid.

3. It allows comparability. As C_{max} is comparable on different layouts for a given network, it can be used to determine which algorithm performs better. Optimization aside, the metric is deterministic, and the benchmark shows that its standard deviation is, in most situations, very low.

4. It shows that layouts capture something of the topological structure of networks. Force-driven placement algorithms are non-deterministic, which means that running them twice does not provide the same result. One might conclude that they are not reliable. Practice tells otherwise, but it is not easy to quantify the similarity between two renderings of the same network, by the same layout algorithm, when all node positions are different. Maximal connected-closeness, as a highly consistent measure of network layouts, proves that force-directed algorithms consistently capture an aspect of the topological structure of the network they represent. I offer a JavaScript implementation of connected-closeness using the library Graphology.[19]

TINKERING 2: A DETERMINISTIC MODEL OF DISTANCES IN NETWORK LAYOUTS

In this tinkering, I endeavor to leverage the ideas of weak ties and local clustering to formalize a notion of community structure that we can state in one sentence in plain English and that can be sufficiently accurate to predict the visual distances in a force-directed layout. This sentence is as follows: "two nodes are close when they are close to the other close nodes in common." Yes, this is self-referential. Allow me to explain step by step.

A LOCAL UNDERSTANDING OF CLUSTERING BASED ON TRANSITIVITY

Our everyday experience of space takes for granted a few things that do not apply to networks, for instance, the weak transitivity of closeness. If Alice is close to Bart and Bart is close to Connie, then Alice is close to Connie—perhaps not as close (hence the "weak") but still pretty close. In fact, a specific property of Euclidean spaces formalizes this: the *triangle inequality*. It states that the distance (AC) cannot be longer than (AB+BC). The physical space of our everyday life is Euclidean, which means that the triangle inequality is true for any three points. While this also holds for any number of dimensions, there are non-Euclidean spaces where the inequality is not necessarily true, notably networks.

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19 *https://observablehq.com/@jacomyma/efficient-implementation-of-connected-closeness*

We can see a network as a space by considering the *geodesic distance*, the length of the shortest path. This distance is said to be "metric" as it respects the triangle inequality and a few other constraints. At first glance, it seems that it might help us understand networks as spaces. Unfortunately, complex networks are characterized by short geodesic distances, as illustrated by the famous "small-world" phenomenon (Milgram, 1967; Watts and Strogatz, 1998). This means that for the geodesic distance, everyone is pretty close to everyone. As a consequence, the geodesic distance is pretty bad at discriminating between nodes. In a complex network, it is extremely approximative. We saw in Chapter 4 that it is a bad model for the Euclidean distances of a force-driven layout. Alternatively, we could use the existence of an edge as a distance: connected is considered close, while disconnected is considered distant. However, this distance discriminates even less than the geodesic distance and it does not satisfy the triangle inequality. More generally, it is not transitive: the neighbors of your neighbors are not necessarily your neighbors.

I value the notion of transitivity for two very different reasons. First, any accurate model of Euclidean distances, like those produced by layout algorithms, must also be weakly transitive. The second reason is because it is part of our intuition about groups. If Alice is in the same group as Bart, and Bart is in the same group as Connie, then there is a chance that Alice and Connie are in the same group. These indirect relations also accumulate. If on one hand Alice is in the same group as Bart, Benjamin, Beyonce, Bonnie, and Brandon, and on the other hand Bart, Benjamin, Beyonce, Bonnie, and Brandon are in the same group as Connie, then it is *highly* probable that Alice and Connie are in the same group. In graph theory, these ABC triangles are called closed triads (note: here, I only consider undirected, unweighted networks). A triad is any group of three nodes, and it is said to be closed when all three nodes are connected. Clusters can be characterized as sets of nodes with a high number of closed triads. Triadic closure (Bianconi et al., 2014; Rapoport, 1953) is important in SNA because it represents the transitivity of human relations: the friends of my friends tend to be my friends. A triad with a missing link, called a *wedge*, is an exception to transitivity: the friend of my friend is not my friend. Wedges are common, even in tight social communities (otherwise, all groups would be cliques). Transitivity can characterize group structures, though not as an absolute rule. Intuitively, you can belong to a group even if you are not friendly with 100% of its members.

Freeman (1992) speaks to the importance of transitivity in his account of "the sociological concept of 'group.'" He notes that "most attempts to specify group structure represent interpersonal linkages in binary, or on/off, terms. Such binary models are unable to capture the variation in peoples' tendencies to get involved with the group" (p. 153). Freeman compares two models: "One, derived by Winship, requires that patterns of social affiliation be strictly transitive. The other, based on Granovetter's ideas about weak and strong ties, requires only a special limited form of transitivity" (p. 152). His empirical testing shows that "the Winship model does not fit the data but that the model developed from Granovetter's work does" (p. 152). The most interesting point is the relation between Granovetter's (1973) famous notion of "weak ties" and transitivity. "Like Winship, Granovetter was concerned with transitivity. But Granovetter qualified that notion. Following Rapoport's reasoning, he proposed that if an individual is *strongly* tied to two others, the two others should be *at least weakly* tied to each other; he was arguing, in effect, that a friend of a friend should be *at least* an acquaintance" (Freeman, 1992: 156).

I operationalize Granovetter's idea that wedges are implicitly closed by a "weak tie." Contrary to Freeman, however, my motivation is not to fit the sociological intuition. My interest is that it fits the weak transitivity of the Euclidean plane. I hypothesize that the appeal of force-directed layouts is due to their ability to manifest implicit weak ties. I concede that this criterion was not part of the motivation of the different layout algorithm designers, not even mine. In fact, I believe that this is accidental. Indeed, it is written nowhere in these algorithms because it is *de facto* enforced by the Euclidean plane where the nodes are placed. In any case, if my hypothesis holds, then it might allow us to say precisely what force-directed layouts make visible.

TINKERING WITH A MODEL FOR LAYOUT DISTANCES

As mentioned earlier, the way we interpret network maps in a topological interpretation regime is by looking at distances between nodes (Figure 74, see also Figure 9). In my intuition, node placement, although necessary for visualization, is not a mandatory step to mediate the topology. Insofar as we only interpret distances, and not the coordinates themselves, then we might be able to transform the network into a set of distances, i.e., a matrix, without the arbitrariness of coordinates. This could not replace visualization in practice as it requires coordinates. However, it might provide a model that predicts visual distances. That model would not be bound by Euclidean constraints, notably the triangle

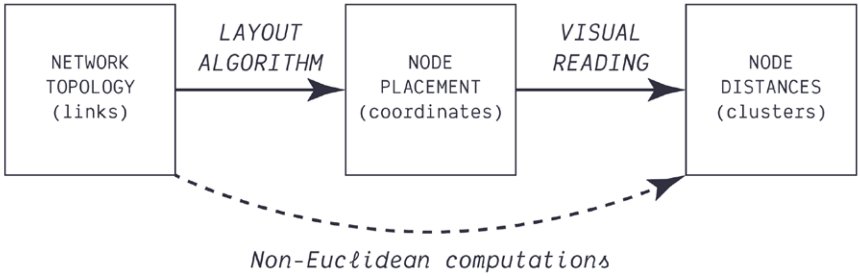

Figure 74. The key steps of rendering a network map. Node coordinates only determine the interpretation via the distances they produce between nodes. Non-Euclidean distances can be computed, but they cannot be visualized as distances.

inequality. I hope that tinkering with transitivity can help us better understand force-driven layouts.

My approach is based on Freeman's (1992) and Granovetter's (1985) intuition that community structure arises from implicit weak links that close wedges as a form of implicit transitivity. The criterion of triadic closure is sometimes called *structural embeddedness* or simply embeddedness (Granovetter, 1985). It is known to generate community structure (Bianconi et al., 2014; Yin et al., 2020), is ingrained in the SNA tradition, and has led to powerful sparsification methods such as the *Simmelian backbone* (Nick et al., 2013; Nocaj et al., 2015). This approach favors triadic closures by removing edges that are involved in too many unclosed wedges. My approach takes the same road but in the opposite direction: following Granovetter's (1985) intuition that some links are implicit, I add weakly weighted links to close wedges, materializing Granovetter's weak transitivity (which I do iteratively). These weak links also become stronger when they close multiple triads. Despite the similarities with the Simmelian backbone, the different strategy leads to different properties. To remain consistent with the notion of embeddedness at the heart of the *Simmelian backbone* technique, I chose to keep the reference to Georg Simmel, but what I build is not a backbone but a latent space (I explain why).

THE SIMMELIAN LATENT SPACE

The metric I propose is presented in the attached document "Simmelian Distance."* It defines a form of node proximity that satisfies the following statement: **two nodes are close either because they are connected or because they are close to the other close nodes in common**. Additionally, I define the Simmelian co-proximity as the same distance, ignoring the fact that the nodes are connected. The Simmelian co-proximity then satisfies the following: **two nodes are close when they are close to the other close nodes in common**. These self-referential statements describe a generalization of embeddedness. The logic of embeddedness is to count triadic closures: for a connected pair, how many triads do they close? In other words, how many common neighbors? The Simmelian proximity generalizes this idea in two ways. First, it does not require the two nodes considered to be connected. It looks for common neighbors, even for disconnected node pairs. Second, the common neighbors it counts are not neighbors in the sense of being connected but in the sense of being close, hence the self-referential formulation. I made it self-referential by design in order to account for the weak transitivity of closeness. The self-referentiality encodes the characteristic transitivity of embeddedness.

Indeed, force-directed layouts are also self-referential because, at equilibrium, the position of each node depends on the position of every other node (through at least the repulsion force). Since I try to model this process, it is not surprising that this model is also self-referential. This requires an iterative process. Nonetheless, contrary to layouts, there is no need to initiate random positions because there are no node positions. The Simmelian distance matrix is initialized with infinite distances between all nodes and converges monotonically, and deterministically, to its limit values. It does not introduce the arbitrariness I pointed to in Chapter 1 (Figure 9). The process and formal proofs are presented in "Simmelian Distance."*

Let me justify why the Simmelian distance defines a latent space. First, the distance defines a semi-metric space: it satisfies almost the same criteria as a Euclidean distance, except the triangle inequality, of which it satisfies a relaxed version. In short:

- The distance is symmetric;
- The distance is null between a node and itself—and only in that case;
- The distance *AC* is always smaller than *k(AB+BC)*, where *k* is a given factor greater than 1.

The Simmelian distance defines a space, and this space is latent. Here, I mean that the Simmelian distance contains *less* information than the network. Despite the fact that we add more links. Intuitively, this is because the Simmelian distance is strongly constrained by its self-referential characterization. It is easy to demonstrate: indeed, different networks can have the same Simmelian distance matrix. In other words, there are fewer Simmelian matrices than networks. In particular, the Simmelian proximity matrix is its own Simmelian reduction. Intuitively, once the non-Simmelian information has been removed, it cannot be removed again. Finding the Simmelian proximity matrix of a network is a reduction, and for this reason, I call it a *latent space*. The proof is presented in "Simmelian Distance."*

EXAMPLES

I did not conduct an extensive benchmark, but I provide a few examples. Figure 75 models the distances in the layout of 21 different networks in three different ways: with embeddedness (counting the common neighbors), with the Simmelian co-proximity distance, and with the Simmelian distance. The two latter distances are defined in "Simmelian Distance."* Their only difference is the

Embeddedness fails with sparse networks

Network	Correlation of Euclidean distance and Structural embeddedness	Correlation of Euclidean distance and Simmelian coproximity Distance	Correlation of Euclidean distance and Simmelian distance
Chain (500n)	-0.01	0.967	0.967
Square Lattice (529n)	-0.2	0.935	0.935
Triangle Lattice (528n)	-0.296	0.938	0.938
Chained 100-cliques (496n)	-0.892	0.963	0.974
Chained 100-cliques (397n)	-0.93	0.945	0.967
Chained 100-cliques (298n)	-0.938	0.888	0.944
Chained 100-cliques (199n)	-0.8	0.7	0.829
Wikipedia-Europe	-0.367	0.417	0.418
C Elegans	-0.408	0.329	0.342
Star (500n)	0.031	-0.031	0.031
Random P=5% (500n)	-0.168	0.181	0.209
Random P=25% (500n)	-0.133	0.11	0.119
Random P=50% (500n)	-0.14	0.118	0.111
SBM Pin=60% (500n)	-0.428	0.331	0.196
SBM Pin=70% (500n)	-0.71	0.679	0.368
SBM Pin=80% (500n)	-0.826	0.845	0.585
SBM Pin=90% (500n)	-0.917	0.939	0.815
SBM Pin=95% (500n)	-0.959	0.975	0.919
SBM Pin=99% (500n)	-0.993	0.997	0.988
SBM Pin=99.9% (500n)	-0.999	0.996	0.996
SBM Pin=99.99% (500n)	-1	0.993	0.993

The layout is not found meaningful for random networks and stars

Embeddedness and Simmelian coproximity correlate with the layout for modular networks

The Simmelian distance performs poorly compared to Simmelian co-proximity and embeddedness for modular networks

Figure 75. 21 networks were rendered by Force Atlas 2 (default settings) except for Wikipedia-Europe (LinLog energy model), then the resulting Euclidean distances were tested for correlation with three distinct models: embeddedness, Simmelian co-proximity distance, and Simmelian distance.

value they take for connected pairs: the Simmelian distance is always 1, while the Simmelian co-proximity distance depends on the other nodes that are close to both nodes of the pair at the same time. As annotated in the figure, four points deserve a highlight. First, embeddedness is a good model for distances as it (anti-)correlates highly with the Euclidean distances in the layout in most situations. However, it completely fails for sparse networks. Indeed, it cannot account for the Euclidean distances of pairs that are not part of triads or at least wedges. Second, the Euclidean distances for certain networks, typically random ones, do not correlate. This follows intuition. Third, the Simmelian co-proximity distance correlates as well as embeddedness for high-modularity networks (in this case, the SBM networks). Fourth, the Simmelian distance generally correlates a little less than its co-proximity variant. I illustrate these points further.

Figure 76 illustrates the case of a square lattice of about 500 nodes. The correlation plot of the structural embeddedness shows why it performs poorly: few node pairs have common neighbors because the network is too sparse. The Simmelian proximity performs much better because it is iterative (self-referential): Simmelian proximities propagate in the network the same way that connected nodes pull each other in a force-directed layout. This is the precise benefit of Granovetter's (1985) weak transitivity.

Figure 77 illustrates the case of an SBM with 2 blocks, an internal link probability of 80% and an external link probability of 20%. As shown in the layout, we have two distinct but heavily bridged clusters. It is worth noting here that the Simmelian distance performed significantly worse than its co-proximity variant. This was due to the many bridges (P_{out} at 20% is relatively high). Each bridge was a long edge and, thus, had a weak co-proximity and embeddedness (the two ends of the bridge belonged to distinct clusters). The Simmelian distance is always 1 for connected pairs, so it fails, by design, to account for long edges. This is why the Simmelian co-proximity generally performs better.

Figure 78 showcases our example network about Europe on *Wikipedia*. Despite this network's high modularity, neither the embeddedness nor the Simmelian co-proximity correlate highly with the Euclidean distance. This suggests that the layout is not very good. I have no good explanation. The correlation plot of structural embeddedness, however, shows another weakness of that metric: like the geodesic distance, it takes a small subset of values in certain contexts, which impairs its ability to correlate with a continuous value. Here, it appears as binning

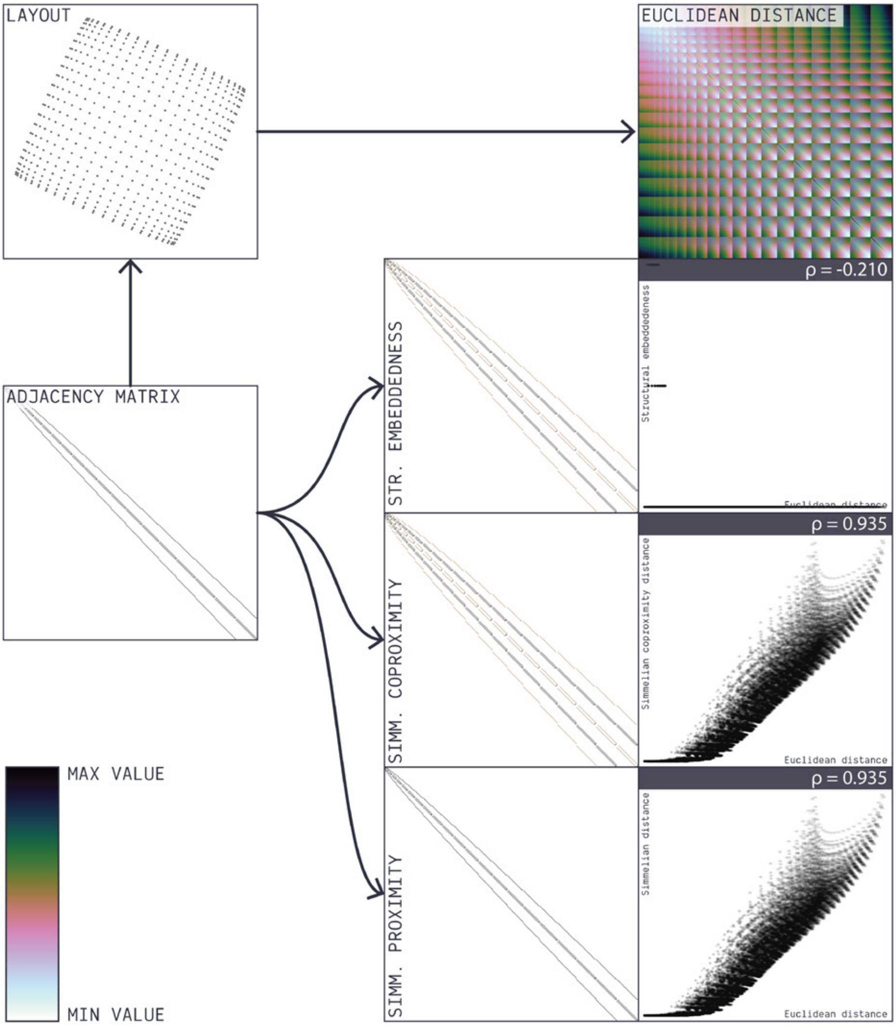

Figure 76. Square lattice. The Euclidean distances were derived from the layout (Force Atlas 2 default settings). The three correlation plots on the right compared the Euclidean distance (X axis) with, on the Y axis and respectively, structural embeddedness, Simmelian co-proximity distance, and Simmelian distance. ρ is the correlation.

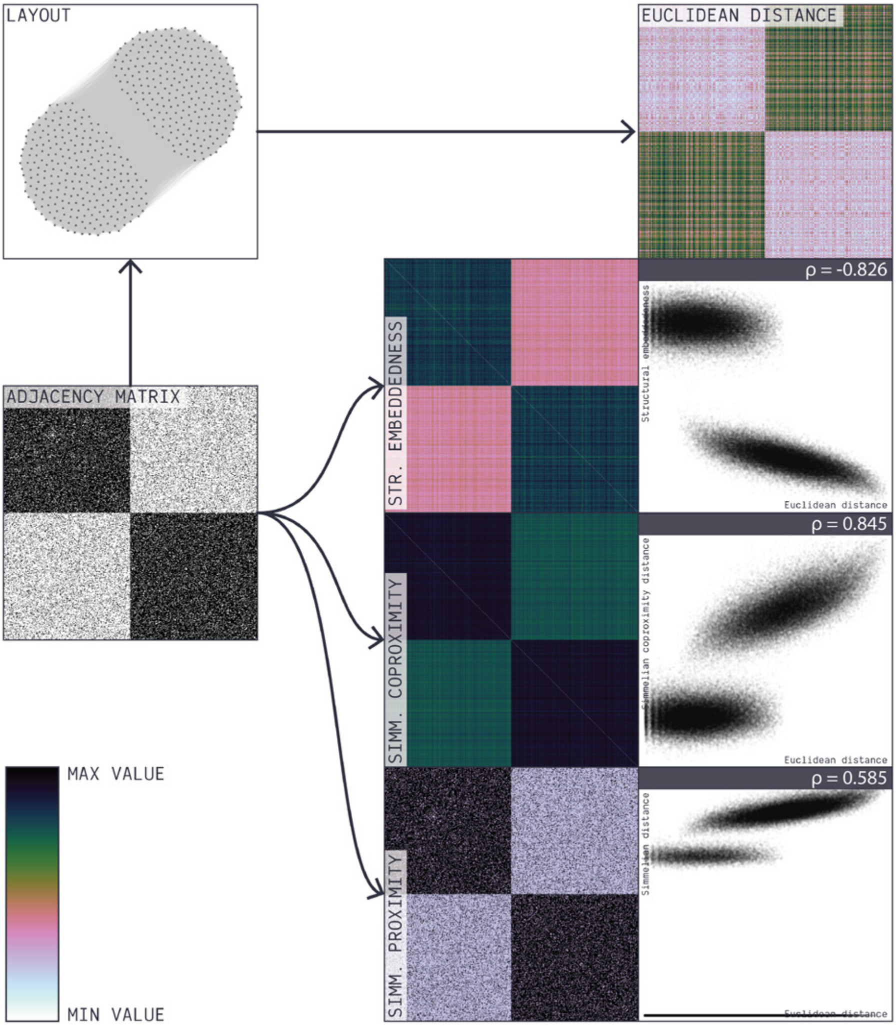

Figure 77. Stochastic block model with 2 blocks, P_{in} = 80% and P_{out} = 20%. The Euclidean distances were derived from the layout (Force Atlas 2 default settings). The three correlation plots on the right compared the Euclidean distance (X axis) with, on the Y axis and respectively, structural embeddedness, Simmelian co-proximity distance, and Simmelian distance. ρ is the correlation.

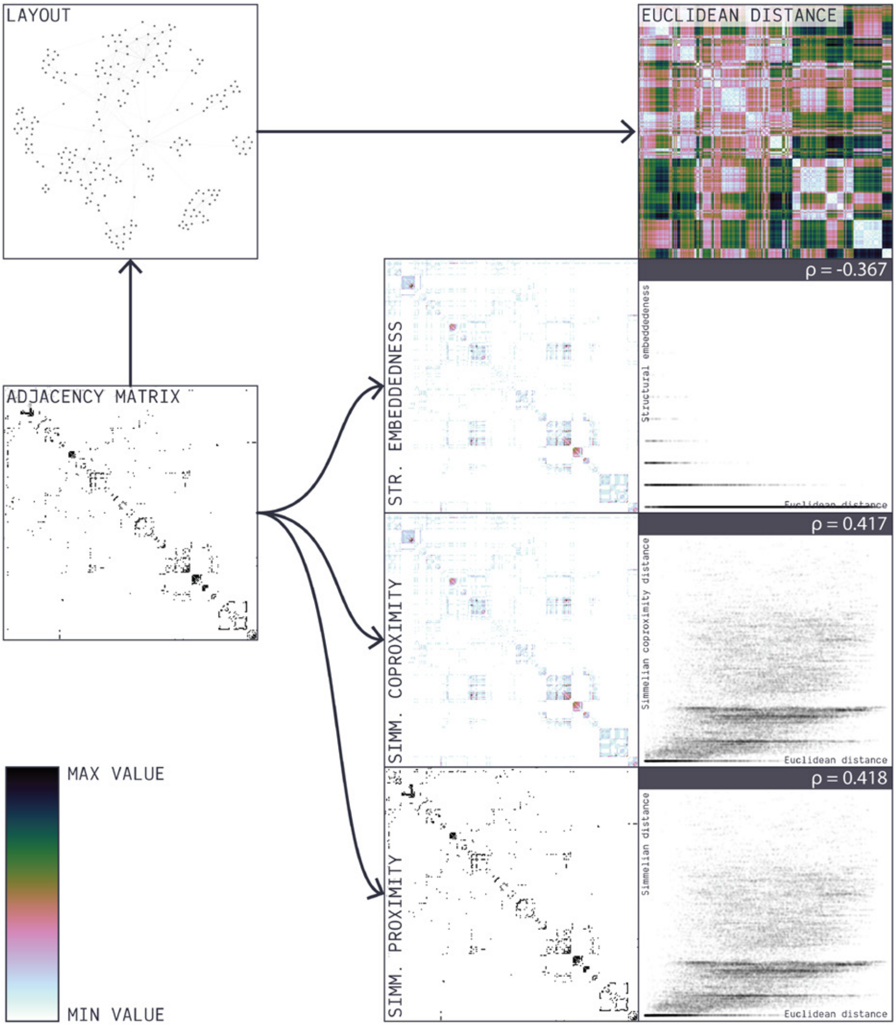

Figure 78. Wikipedia-Europe. The Euclidean distances were derived from the layout (Force Atlas 2 with LinLog enabled). The three correlation plots on the right compared the Euclidean distance (X axis) with, on the Y axis and respectively, structural embeddedness, Simmelian co-proximity distance, and Simmelian distance. ρ is the correlation.

along the Y axis. I assume that this is due to the small size of the clusters, which limits the number of possible common neighbors. The Simmelian distance (and co-proximity) is, in comparison, much more nuanced. The difference it makes is not huge, but it is still notable.

Figure 79 illustrates a stretching: a chained 100-clique of about 500 nodes. Once again, the correlation plots show the limitations of embeddedness, struggling here to qualify the pairs of nodes too distant to have a common neighbor. Something else is remarkable: the correlation with the Simmelian co-proximity distance (and the Simmelian distance) is very high. In this case, the Simmelian co-proximity distance is an extremely good model of the Euclidean distance. This suggests that the Simmelian co-proximity distance could be used as a benchmark to compare different layouts, at least for this type of network.

DISCUSSION

The Simmelian distance is a promising concept. As we argue in "What Do We See When We Look at Networks?"* a layout quality metric should also be declined at the node and edge level. Assuming that a more systematic benchmark confirms the properties of the metric, we could analyze a layout more finely: which edges, nodes, or areas are most distorted? We could do many things. My hope is that, someday, scholars will be able to legitimize their network maps with objective statements such as "nodes that are close in this layout correlate at 90% with being close to the other close nodes in common" or any other statement that is sufficiently short to provide context. Surely, certain networks are poorly represented (dense, random networks?), while others are well represented (stretchings?), and we deserve to know. Nonetheless, operationalizing a layout quality metric also begs subtle questions. The quality metric demarcates right from wrong. What kind of layout reality does it perform?

I have warned about this: the Simmelian distance is just one among several possible models, and each model comes with its own ideal and statement about what a layout "should" be. We can already see it here because the Simmelian latent space comes in two distinct flavors: basic and co-proximity. The co-proximity version ignores the presence of a link between two edges, while the basic version takes it in account by setting the distance to 1. Which one is better? I have shown that the co-proximity correlates better; however, does it make it better? This is a strategic choice with implications that do not produce a clearly better option. Setting the standard as the co-proximity version validates the length of long

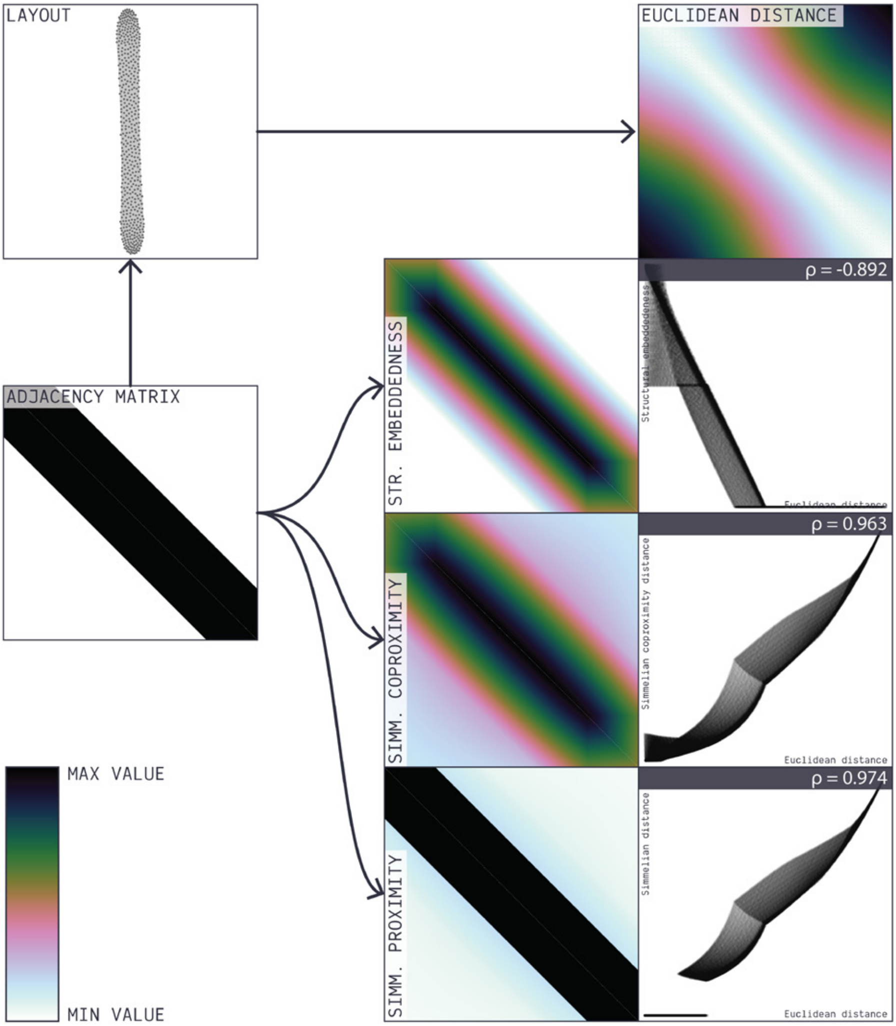

Figure 79. Chained 100-cliques with 496 nodes. The Euclidean distances were derived from the layout (Force Atlas 2 default settings). The three correlation plots on the right compared the Euclidean distance (X axis) with, on the Y axis and respectively, structural embeddedness, Simmelian co-proximity distance, and Simmelian distance. ρ is the correlation.

edges. It states that a connection can be dismissed if it is not confirmed by common neighbors. It dismisses bridges, and by doing so, it is also more Euclidean, better respecting the triangle inequality. On the contrary, setting the standard as the basic version maintains the non-Euclidean nature of the network. It maintains bridges as shortcuts, even though it means that they break open the triangle inequality: clusters are distant, yet through bridges, they are close. It casts long edges as distortions or failures of the layout—necessary failures, maybe, but failures nonetheless. Who should decide what is the proper status of bridges? We need not decide; we might just stay put with the trouble. I do not think that network practices would have the use of a normative position, but the discussion is worth it. This is how we situate our own practices and, from there, our knowledge production.

6. CONCLUSION: FROM COMPLEXOSCOPES TO COMPLEXOSCAPES

In this thesis, I have explained that VNA is a practice built on top of multiple fields that do not necessarily agree on what a network is or what a community is. I have also argued that practices have a life of their own, independent of the agenda of algorithm designers and methodological experts (among other actors). We observed this in Gephi's subculture, but it is more generally part of our relation with scientific instruments. I have shown that the methodologists who endeavored to evaluate graph drawings have been constantly topped by the innovations of algorithm designers, who acknowledged the methodologists while politely ignoring their recommendations. I have formalized this disconnection as two distinct regimes of interpretation, *diagrammatic*, for the older readability-oriented aesthetic criteria, and *topological*, for the more recent fashion of mediating network structure through node placement. This change was not triggered by methodological reflections but by the sudden availability of large empirical complex networks and the emergence of the field of network science, as I narrated in "Epistemic Clashes in Network Science."* I proposed a Gestalt model of how we see networks and showed that it did not match the notion of grouping implemented by layout algorithms. More generally, I criticized the reasons offered by algorithm designers to justify the quality of their algorithms. I contended that their justifications often reflected their intent and did not assess what the algorithm actually performed. I argued, in particular, that the literature on community detection adopted a rhetoric that performs communities as partitions and omits other forms of community structure. I have tried to reclaim these other forms under the name *stretchings*—community-like structures that are more extensive than the typical cluster yet cannot be divided into high-modularity parts. I proposed two interventions to help scholars deal with the interpretation of their network maps. The first offered a scale to quantify the relation between the distances in the picture and the topological structure. The second proposed a model for distances in a force-directed layout, which could help determine which networks are well represented and which are not—assuming that we can spell out what a good mediation is.

As a conclusion, I offer a few words on the meaning of this research beyond the question of networks. In this dissertation, I considered only the simplest of networks: undirected, monopartite (one type of node), monolayer (one type of edge), with no hyperedges (edges that connect more than 2 nodes), static (no time dimension), etc. Researchers have developed many specialized perspectives on networks, for example, socio-semantic networks (Roth and Cointet, 2010), multilevel network analysis (hierarchically nested networks) (Lazega and Snijders, 2015), and networks of networks (D'Agostino and Scala, 2014), to name a few. For an overview, Kivelä et al. (2014) discuss the history of multilayer networks (and related concepts) and review the exploding body of work on such networks. This plethora shows the interest of researchers in exploring conceptual variations of networks. These works generally make the argument that a more sophisticated network model is more suitable to certain phenomena or situations. For instance, Cambrosio et al. (2020) defend, in an STS context, that hypergraphs (networks with hyperedges) "more closely adhere to the specifications of a sociology of translation" (p. 1020). In their view, simple networks are insufficient to operationalize actor–network theory. Each approach requires an adaptation of network visualization techniques. Nonetheless, drawing large simple networks has remained problematic. Innovating techniques and tools have been developed to fulfil emergent needs, followed, with a decade-long delay, by the critical re-examination of methodologies that were *de-facto* employed to perform network analysis. As I argued in Chapter 3, the evaluation of graph drawing has always followed the practice. I see this dynamic as largely inevitable and not as problematic as it may seem. Indeed, years of engagement with VNA now allow us to better assess the situation. Part of this endeavor is to take a step back and consider NA from other angles than the practical necessity of visualizing large networks, which was so pressing 12 years ago. This dissertation focused on NA and visualization, but as a tool maker, I am generally more interested in our relation with scientific instruments. Furthermore, on that matter, the situation of VNA offers a few interesting things to reflect on.

The central and most interesting point for me is the fundamental difference between an instrument such as Gephi and a telescope or a microscope. Optical magnification provides a standpoint from which we can understand the observed phenomenon quite naturally. A telescope makes the Moon closer and smaller, as if it were a ball; if you prefer, it makes us bigger. Either way, the standpoint is easy to understand, and we intuitively grasp the limitations of the mediation. For instance, we do not see the dark side of the Moon or its insides because these limitations also apply in our everyday experience. Network visualization works differently because we do not have an everyday visual experience of networks. I must guard against a misunderstanding here because you might think that we have grown accustomed to networks by being exposed to many network maps. However, network maps are not a natural experience of networks, notably because the drawn link has a length while the topological link is as dimensionless as a point. Links are more dot-like than line-like, but we have to sacrifice this aspect to draw a network map. Conversely, in a matrix visualization, links are dot-like; it is the nodes that sacrifice their dot-likeness, manifested as rows and columns. There are always trade-offs because our cognition is accustomed to the Euclidean space, while networks are generally non-Euclidean. Network visualization has no choice but to sacrifice more features of networks than a lens sacrifices features of the Moon. It involves more layers of mediation than optical magnification does because networks have a smaller fit to our cognitive abilities than objects that are simply too far away or too small. While the telescope virtualizes a relatively realistic standpoint (it seems to just make us bigger or smaller), network visualization needs to invent a whole new standpoint. This standpoint invented by network maps is just one of many possibilities, each with their own benefits and issues (e.g., matrices). I have argued throughout this dissertation that the layers of mediation involved in network maps are difficult to account for and remain partially inaccessible to many of those who craft or read network visualizations. There is no doubt that mediating a network is more complicated than mediating the Moon. However, network visualization is not just quantitatively different from optical magnification; it is also qualitatively different. It is faced with a completely new problem: the inevitable reduction of the phenomenon represented.

In the topological interpretation regime, the node placement acts as a reduction of the network (not in the diagrammatic interpretation regime, see Chapter 3). As I argued in Chapter 4, force-driven placement sacrifices certain edges (the long ones in the resulting placement) in order to manifest the community structure as node distances: topological clusters tend to produce visual clusters, but as I argued in Chapter 5, it is important to acknowledge that community structures are poorly characterized as sets of clusters. Node placement is a reduction because it only partially and imperfectly reflects the features of the network. The information omitted through this reduction can still be represented by drawing the links, but it does not help in practice because there are too many of them. Our cognitive abilities are easily overwhelmed by networks, due less to their size than their complexity—their entanglement. For instance, it is the entanglement of clusters that makes community detection problematic. Modularity clustering (Newman and Girvan, 2004) aims to optimize modularity (Newman, 2004), and we can assess the quality of the reduction by looking at the modularity score: if it is very close to 100%, then we can reasonably describe the network as the set of clusters obtained. This is an oversimplification, but it does not matter because, in practice, the networks we visualize never reach a modularity close to 100%. The recurrent example of this dissertation, *Wikipedia*-Europe (Figure 5), despite a caricatural community structure, only reached a modularity of 78% (Figure 68) through community detection. The clusters were easy to identify, yet many links connected them—entangled them. Most empirical networks are too intricate to be fully described by simple models. I highlight this point because computer scientists may be tempted to have a realistic interpretation of the reductions they perform, thus assuming that networks are a true mix of structure (features that can be modeled) and noise (features that cannot); I addressed the rhetoric of structure extraction in Chapter 4. However, the study of empirical networks (e.g., SNA) is generally aimed at minimizing assumptions and refraining from discarding certain network features for the sole motive that they get statistical models into trouble. It is neither surprising nor specific to network phenomena that statistical modeling discards information, yet in this case, *visualization*, *too*, requires it. Reduction is expected of statistical metrics, less so of visualization. However, the challenge of force-driven layouts illustrates it: no visualization of a sufficiently large complex network may allow interpreting the topological structure without performing a reduction.

Visualization is often presented as a complement to reductionist strategies, either because they lose information or because they necessitate assumptions. “Vis allows people to analyze data when they don’t know exactly what questions they need to ask in advance,” writes Munzner (2014: 2), and she adds: “Statistical characterization of datasets is a very powerful approach, but it has the intrinsic limitation of losing information through summarization” (p. 6). Fekete et al. (2008: 14) make the same point: “Is there a competition between confirmatory, automated and exploratory methods? No, they answer different questions. When a model is known in advance or expected, using statistics is the right method. When a dataset becomes too large to be visualized directly, automating some analysis is required. When exploring a dataset in search of insights, information visualization should be used, possibly in conjunction with data mining techniques if the dataset is too large.” This point (see Behrens and Yu, 2003; Fekete et al., 2008; Foucault Welles and Meirelles, 2015; Munzner, 2014; Rieder and Röhle,

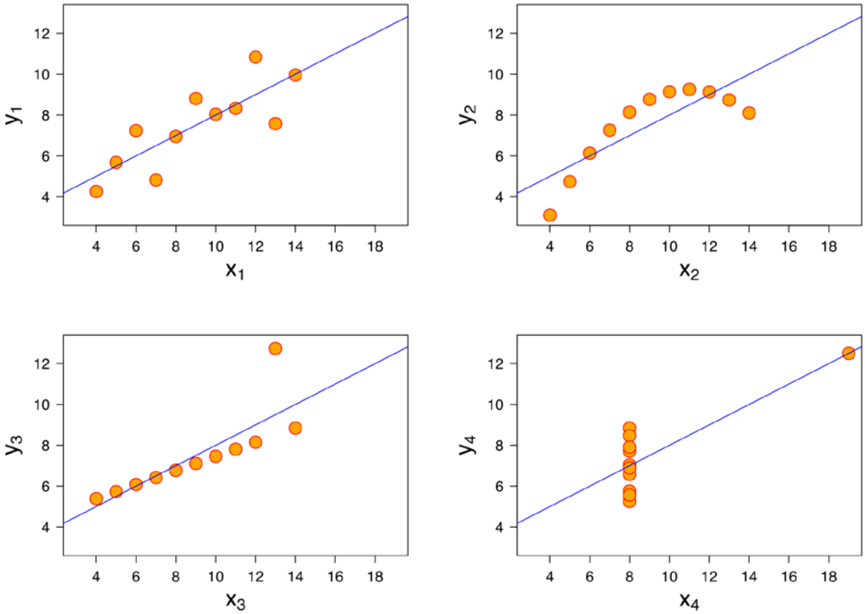

Figure 80. The four-data series defined by Anscombe (1973), for which some of the usual statistical properties (mean, variance, correlation and regression line) are the same. Visualization by Schutz, licensed under CC-BY-SA.

2017) is often illustrated by Anscombe's (1973) famous quartet (Figure 80). Such a simple example can make it clear that reduction is at risk of discarding the most important information, while visualization provides a more exhaustive perspective. Visualization is valued as a complement to the weakness of statistical reductions: unmanaged information loss. This is precisely where network visualization faces a brand new challenge: in this case, *visualization*, *too*, performs a reduction and generates unmanaged information loss. Of course, it does not make visualization irrelevant. In Chapter 4, I argued that force-driven layouts perform a reduction that is different and, in certain ways, better than clustering algorithms. However, it challenges the assumption that visualization may always provide an exhaustive and neutral view over the visualized phenomenon, an assumption that Haraway (1988: 581) called the "god trick of seeing everything from nowhere."

A Gephi user once told me: "Gephi understands the network, but I do not understand Gephi." I understand this statement as an acknowledgement that the visualization is correct despite being incomprehensible. This point is crucial because as long as we frame unintelligible images as visualization failures, as long as we assume that a yet unknown technique would allow us to see all there is to see, we refuse to face that increasingly large and complex data will inevitably surpass our cognitive abilities. No visualization technique can prevent that. Visualization techniques will require increasingly strong reductions and more and more layers of mediation. The simplest needs such as storing, counting, and monitoring will require reductions, and the lack of overview will make it increasingly difficult to assess the unknown unknowns inherent to these reductions. Complex networks have only foreshadowed this turn to complex visualizations. The field of machine learning is now facing the situation that what a neural network has learned lies in such large and entangled data that sophisticated information systems, such as "activation atlases" (Carter et al., 2019), are necessary to monitor them (Olah et al., 2017; Yosinski et al., 2015).

As a tool maker, I offer this takeaway: we cannot build complexo*scopes*. The metaphor of optical magnification is misleading when it comes to building scientific instruments to study complex phenomena. Telescopes and microscopes, as archetypal scientific instruments, have made us accustomed to seeing into the distance as if it were close and into the tiny as if it were large. However, we cannot see into the complex as if it were simple. We must switch metaphors and build our scientific apparatus from a different perspective. We must build something else, for instance, complexo*scapes*—composite visualization systems where inevitable reductions are counterbalanced by the possibility of navigating between complementary views and visualizations.

REFERENCES

Adamic, L.A. and Glance, N. (2005) ‘The political blogosphere and the 2004 U.S. election: Divided they blog’, in *Proceedings of the 3rd International Workshop on Link Discovery (LinkKDD ’05)*. New York, NY: Association for Computing Machinery, pp. 36–43. doi:10.1145/1134271.1134277.

Adar, E. (2006) ‘GUESS: A language and interface for graph exploration’, in *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, pp. 791–800. doi:10.1145/1124772.1124889

Albert, R., Jeong, H. and Barabási, A.-L. (1999) ‘The diameter of the World Wide Web’, *Nature*. 401(6749), pp. 130–131. doi:10.1038/43601.

Anderson, C. (2008) ‘The end of theory: The data deluge makes the scientific method obsolete’, *Wired Magazine*, 16(7), pp.16–07.

Andris, C., Lee, D., Hamilton, M.J., Martino, M., Gunning, C.E. and Selden, J.A. (2015) ‘The rise of partisanship and super-cooperators in the U.S. House of Representatives’, *PLoS ONE*, 10(4), e0123507. doi:10.1371/journal.pone.0123507.

Anscombe, F.J. (1973) ‘Graphs in statistical analysis’, *The American Statistician, 27*(1), pp. 17–21.

Aragón, P., Kappler, K.E., Kaltenbrunner, A., Laniado, D. and Volkovich, Y. (2013) ‘Communication dynamics in twitter during political campaigns: The case of the 2011 Spanish national election’, *Policy & Internet*, 5(2), pp. 183–206.

Bachimont, B. (2004) ‘Arts et sciences du numérique: ingénierie des connaissances et critique de la raison computationnelle’, Mémoire d’Habilitation à Diriger des Recherches.

Barabási, A.L. (2016) *Network science*. Cambridge: Cambridge University Press.

Barabási, A.L. and Albert, R. (1999) ‘Emergence of scaling in random networks’, *Science*, 286(5439), pp. 509–512.

Barabasi, A.L. and Oltvai, Z.N. (2004) ‘Network biology: Understanding the cell’s functional organization’, *Nature Reviews Genetics*, 5(2), pp. 101–113.

Barnes, J.A. and Harary, F. (1983) ‘Graph theory in network analysis’, *Social Networks*, 5(2), pp. 235–244.

Barthes, R. (1981) *Camera lucida: Reflections on photography*. London: Macmillan.

Bastian, M., Heymann, S. and Jacomy, M. (2009) ‘Gephi: An open source software for exploring and manipulating networks’, in *Third International ICWSM Conference*, San Jose, California, USA, 17–20 May 2009, pp. 361–362. Available at: http://www.aaai.org/ocs/index.php/ICWSM/09/paper/viewFile/154/1009/ (Accessed: 13 March 2017).

Batini, C., Furlani, L. and Nardelli, E. (1985) ‘What is a good diagram? A pragmatic approach’, *Fourth International Conference on Entity-Relationship Approach*, Chicago, Illinois, USA. IEEE Computer Society, pp. 312–319.

Behrens, J.T. and Yu, C.-H. (2003) ‘Exploratory data analysis’, in Weiner, I.B. (ed.), *Handbook of psychology*. London: Wiley, pp. 33–64. doi:10.1002/0471264385.wei0202.

Behrisch, M., Bach, B., Henry Riche, N., Schreck, T. and Fekete, J.-D. (2016) ‘Matrix reordering methods for table and network visualization’, in *Computer Graphics Forum*, 35(3), pp. 693–716.

Behrisch, M., Blumenschein, M., Kim, N.W., Shao, L., El-Assady, M., Fuchs, J., Seebacher, D., Diehl, A., Brandes, U., Pfister, H., Schreck, T., Weiskopf, D. and Keim, D.A. (2018) ‘Quality metrics for information visualization’, *Computer Graphics Forum*, 37(3), pp. 625–662. doi:10.1111/cgf.13446.

Bennett, C., Ryall, J., Spalteholz, L. and Gooch, A. (2007) ‘The aesthetics of graph visualization’, in *Proceedings of the 2007 Computational Aesthetics in Graphics, Visualization, and Imaging*, Banff, Alberta, Canada, 20–22 June 2007, pp. 57–64. doi:10.2312/COMPAESTH/COMPAESTH07/057-064.

Bertin, J. (1967) *Sémiologie Graphique. Les diagrammes, les réseaux, les cartes*. Paris: La Haye, Mouton, Gauthier-Villars.

Bianconi, G., Darst, R.K., Iacovacci, J. and Fortunato, S. (2014) ‘Triadic closure as a basic generating mechanism of communities in complex networks’, *Physical Review E – Statistical, Nonlinear, and Soft Matter Physics*, 90(4), 42806. doi:10.1103/PhysRevE.90.042806.

Blondel, V.D., Guillaume, J.-L., Lambiotte, R. and Lefebvre, E. (2008) ‘Fast unfolding of communities in large networks’, *Journal of Statistical Mechanics: Theory and Experiment*, 2008(10). doi:10.1088/1742-5468/2008/10/P10008.

Blythe, J., McGrath, C. and Krackhardt, D. (1996) ‘The effect of graph layout on inference from social network data’, in *Lecture notes in computer science*. Berlin, Heidelberg: Springer Verlag, pp. 40–51. doi:10.1007/bfb0021789.

Borgatti, S.P., Mehra, A., Brass, D.J. and Labianca, G. (2009) ‘Network analysis in the social sciences’, *Science*, 323(5916), pp. 892–895.

Börner, K., Sanyal, S. and Vespignani, A. (2007) ‘Network science’, *Annual Review of Information Science and Technology*, 41(1), pp. 537–607.

Boullier, D., Crépel, M. and Jacomy, M. (2016) ‘Zoomer n’est pas explorer’, *Réseaux*, 195(1), pp. 131–161. doi:10.3917/res.195.0131.

Bounegru, L., Venturini, T., Gray, J. and Jacomy, M. (2017) ‘Narrating networks: Exploring the affordances of networks as storytelling devices in journalism’, *Digital Journalism*, 5(6), pp. 699–730. doi:10.1080/21670811.2016.1186497.

Brandes, U. and Erlebach, T. (2005) ‘Introduction’, in Brandes U. and Erlebach T. (eds.), *Network analysis. Lecture notes in computer science*. Berlin, Heidelberg: Springer, vol. 3418. doi:10.1007/978-3-540-31955-9_1

Brandes, U. and Pich, C. (2009) ‘An experimental study on distance-based graph drawing’, in Tollis I.G. and Patrignani M. (eds.), *Graph Drawing. GD 2008. Lecture Notes in Computer Science.* Berlin, Heidelberg: Springer, vol. 5417. doi:10.1007/978-3-642-00219-9_21

Brandes, U. and Wagner, D. (2004) ‘Analysis and visualization of social networks’, in Jünger, M. and Mutzel, P. (eds.), *Graph drawing software*. Berlin, Heidelberg: Springer, pp. 321–340. Available at: http://www.uni-konstanz.de/algo/publications/bw-vavsn-04.pdf (Accessed: 26 June 2019).

Brandes, U., Robins, G., McCranie, A. and Wasserman, S. (2013) 'What is network science?' *Network Science*, 1(1), pp. 1–15.

Brockmann, D. (2018) *Complexity explorable: A patchwork Darwinge.* Available at: https://www.complexity-explorables.org/explorables/a-patchwork-darwinge/ (Accessed: 09 December 2020).

Bruns, A. (2012) 'How long is a tweet? Mapping dynamic conversation networks on Twitter using Gawk and Gephi', *Information, Communication & Society*, 15(9), pp. 1323–1351.

Bruns, A. (2013) 'Faster than the speed of print: Reconciling 'big data' social media analysis and academic scholarship', *First Monday*, 18(10). Available at: http://firstmonday.org/ojs/index.php/fm/article/view/4879 (Accessed: 20 October 2020).

Butts, C.T. (2009) 'Revisiting the foundations of network analysis', *Science*, 325(5939), pp. 414–416.

Calatayud, J., Bernardo-Madrid, R., Neuman, M., Rojas, A. and Rosvall, M. (2019) 'Exploring the solution landscape enables more reliable network community detection', *Physical Review E*, 100(5), 052308.

Callon, M., Law, J. and Rip, A. (1986) 'Qualitative scientometrics', in Callon, M., Law, J. and Rip, A. (eds.), *Mapping the dynamics of science and technology*. Houndmills: Macmillan, pp. 103–123.

Cambrosio, A., Cointet, J.-P. and Abdo, A.H. (2020) 'Beyond networks: Aligning qualitative and computational science studies', *Quantitative Science Studies*, 1(3), pp. 1017–1024. doi:10.1162/qss_a_00055.

Campagnolo, G.M. (2020) *Social data science Xennials: Between analogue and digital*. Cham: Springerp. doi:10.1007/978-3-030-60358-8_3.

Cardon, D., Cointet, J.-P., Ooghe, B. and Plique, G. (2019) 'Unfolding the multi-layered structure of the French mediascape'. Available at: https://spire.sciencespo.fr/hdl:/2441/52avseho8m9rjbmeot0eogd0iu/resources/wp1medialab-unfolding-the-multi-layered-structure-of-french-media-landscape-vf-2.pdf (Accessed: 26 October 2020).

Carter, S., Armstrong, Z., Schubert, L., Johnson, I. and Olah, C. (2019) 'Activation atlas', *Distill*, 4(3).

Chiesi, A.M. (2015) 'Network analysis', in Wright, J.D. (ed.), *International encyclopedia of the social & behavioral sciences*, pp. 518–523. doi:10.1016/B978-0-08-097086-8.73055-8

Christakis, N.A. and Fowler, J.H. (2009) *Connected: The surprising power of our social networks and how they shape our lives*. New York, USA: Little, Brown Spark.

Collins, H.M. (1981) 'Son of seven sexes: The social destruction of a physical phenomenon', *Social Studies of Science*, 11(1), pp. 33–62.

Contandriopoulos, D., Larouche, C., Breton, M. and Brousselle, A. (2017) 'A sociogram is worth a thousand words: Proposing a method for the visual analysis of narrative data', *Qualitative Research*, 18(1), pp. 70–87.

Correa, C.D. and Ma, K.-L. (2011) 'Visualizing social networks', in Aggarwal, C.C. (ed.), *Social network data analytics*. Boston, MA: Springer, pp. 307–326. doi:10.1007/978-1-4419-8462-3_11.

Cristea, I.A. and Ioannidis, J.P. (2018) ‘P values in display items are ubiquitous and almost invariably significant: A survey of top science journals’, *PloS ONE*, 13(5), e0197440.

D’Agostino, G. and Scala, A. (eds.) (2014) *Networks of networks: The last frontier of complexity*. Berlin: Springer, vol. 340.

Davidson, R. and Harel, D. (1996) ‘Drawing graphs nicely using simulated annealing’, *ACM Transactions on Graphics*, 15(4), pp. 301–331

Decuypere, M. (2020) ‘Visual network analysis: A qualitative method for researching sociomaterial practice’, *Qualitative Research*, 20(1), pp. 73–90. doi:10.1177/1468794118816613.

Dianati, N. (2016) ‘Unwinding the hairball graph: Pruning algorithms for weighted complex networks’, *Physical Review E*, 93(1), 012304.

Di Battista, G., Eades, P., Tamassia, R. and Tollis, I.G. (1994) ‘Algorithms for drawing graphs: An annotated bibliography’, *Computational Geometry*, 4(5), pp. 235–282.

Diminescu, D. (2008) ‘The connected migrant: An epistemological manifesto’, *Social Science Information*, 47(4), pp. 565–579.

Diminescu, D. (2012) ‘Diasporas on the web’, *Social Science Information*, 51(4), pp. 451–694.

Diminescu, D., Bourgeois, M., Renault, M. and Jacomy, M. (2011) ‘Digital diasporas atlas exploration and cartography of diasporas in digital networks’, *Fifth International AAAI Conference on Weblogs and Social Media*, Barcelona, Spain, 17–21 July 2011, pp. 657–658.

Diminescu, D., Asal, H., Balalovska, K., Ben-David, A., Berthomière, W., Bruslé, T., Carsignol, A., Gangloff, S., Graziano, T., Knaute, D., Kumar, P., Le Bayon, S., Leclerc, É., Ma Mung Kuang, E., Marchandise, S., Mazzucchelli, F., Morgunova, O., Moua, M.H., Percot, M., Renault, M., Reyhan, D., Scioldo Zürcher, Y., Severo, M., Therwath, I., Varrel, A., Venier, P., Watin, M., Wolff, E. and Zuolo, E. (2012) ‘e-Diasporas atlas’. Available at: http://www.e-diasporas.fr (Accessed: 18 August 2020).

Drucker, J. (2014) *Graphesis: Visual forms of knowledge production*. Cambridge, MA: Harvard University Press.

Dunne, C. and Shneiderman, B. (2009) ‘Improving graph drawing readability by incorporating readability metrics: A software tool for network analysts’, *HCIL Tech Reports (HCIL-2009-13)*, pp. 1–9. Available at: www.visualcomplexity.com (Accessed: 24 June 2019).

Eades, P. (1984) ‘A heuristic for graph drawing’, *Congressus Numerantium*, 42, pp. 149–160. Available at: https://ci.nii.ac.jp/naid/10000023432 (Accessed: 13 October 2020).

Eades, P. (2014) ‘What is a good diagram (revisited)?’ in *2014 IEEE Symposium on Visual Languages and Human-Centric Computing (VL/HCC)*, Melbourne, Australia, 28 July–1 August 2014, IEEE, pp. 1-2.

Eades, P. and Tamassia, R. (1987) ‘Algorithms for drawing graphs: An annotated bibliography’, Technical Report No. 82, Department of Computer Science, University of Queensland, Australia.

Edge, D., Larson, J., Mobius, M. and White, C. (2018) ‘Trimming the hairball: Edge cutting strategies for making dense graphs usable’, in *2018 IEEE International Conference on Big Data (Big Data)*, Seattle, WA, USA, 10–13 December 2018, IEEE, pp. 3951–3958.

Erdős, P. and Rényi, A. (1960) 'On the evolution of random graphs', *Publications of the Mathematical Institute of the Hungarian Academy of Sciences*, 5(1), pp. 17–60.

Euler, L. (1736) 'Solutio problematis ad geometriam situs pertinentis', *Commentarii Academiae Scientiarum Petropolitanae*, 8, pp. 128–40.

Erikson, E. (2013) 'Formalist and relationalist theory in social network analysis', *Sociological Theory*, 31(3), pp. 219–242. doi:10.1177/0735275113501998.

Fekete, J.-D., Van Wijk, J.J., Stasko, J.T. and North, C. (2008) 'The value of information visualization', in Kerren, A., Stasko, J.T., Fekete, J.-D. and North, C. (eds.), *Information visualization*. Berlin, Heidelberg: Springer, pp. 1–18.

Føllesdal, D. (1969) 'Husserl's notion of noema', *The Journal of Philosophy*, 66(20), pp. 680–687.

Fortunato, S. (2010) 'Community detection in graphs', *Physics Reports*, pp. 75–174. doi:10.1016/j.physrep.2009.11.002.

Foucault Welles, B. and Meirelles, I. (2015) 'Visualizing computational social science: The multiple lives of a complex image', *Science Communication*, 37(1), pp. 34–58.

Fouss, F., Pirotte, A., Renders, J.-M. and Saerens, N. (2007) 'Random-walk computation of similarities between nodes of a graph with application to collaborative recommendation', *IEEE Transactions on Knowledge and Data Engineering*, 19(3), pp. 335–69.

Freeman, L.C. (1992) 'The sociological concept of 'group': An empirical test of two models', *American Journal of Sociology*, pp. 152–166.

Freeman, L.C. (2008) 'Going the wrong way on a one-way street: Centrality in physics and biology', *Journal of Social Structure*, 9(2), pp. 1–15.

Frick, A., Ludwig, A. and Mehldau, H. (1995) 'A fast adaptive layout algorithm for undirected graphs (extended abstract and system demonstration)', *Graph drawing*. Available at: http://ai2-s2-pdfs.s3.amazonaws.com/9168/79db7769e9978ad8628f17b05798a5d2bf82.pdf (Accessed: 18 April 2017).

Früchterman, T.M.J. and Reingold, E.M. (1991) 'Graph drawing by force-directed placement', *Software: Practice and Experience*, 21(11), pp. 1129–1164. doi:10.1002/spe.4380211102.

Gajer, P. and Kobourov, S.G. (2001) 'GRIP: Graph drawing with intelligent placement', in Marks, J. (ed.), *Graph Drawing. GD 2000. Lecture notes in computer science*, vol. 1984. Berlin: Springer Verlag, pp. 222–228. doi:10.1007/3-540-44541-2_21.

Gansner, E.R., Koren, Y. and North, S. (2004) 'Graph drawing by stress majorization', in Pach, J. (ed.), *Graph Drawing. GD 2004. Lecture notes in computer science*, vol. 3383. Berlin: Springer Verlag, pp. 239–250. doi:10.1007/978-3-540-31843-9_25.

Ghitalla, F., Diemert, E., Maussang, C. and Pfaender, F. (2004) 'Tarente: An experimental tool for extracting and exploring web aggregates', in *Proceedings: 2004 International Conference on Information and Communication Technologies: From Theory to Applications*, Damascus, Syria, 23–23 April 2004. IEEE, pp. 627–628.

Ghoniem, M., Fekete, J.-D. and Castagliola, P. (2005) 'On the readability of graphs using node-link and matrix-based representations: A controlled experiment and statistical analysis', *Information Visualization*, 4(2), pp. 114–135. doi:10.1057/palgrave.ivs.9500092.

Gibson, H., Faith, J. and Vickers, P. (2012) 'A survey of two-dimensional graph layout techniques for information visualisation', *Information Visualization*, 12(3-4), pp. 324–357. doi:10.1177/1473871612455749.

Good, B.H., De Montjoye, Y.A. and Clauset, A. (2010) 'Performance of modularity maximization in practical contexts', *Physical Review E – Statistical, Nonlinear, and Soft Matter Physics*, 81(4), 046106. doi:10.1103/PhysRevE.81.046106.

Grandjean, M. (2016). 'A social network analysis of Twitter: Mapping the digital humanities community', *Cogent Arts & Humanities*, 3(1), 1171458.

Grandjean, M. and Jacomy, M. (2019) 'Translating networks: Assessing correspondence between network visualisation and analytics', in *Digital Humanities Conference*, Utrecht, Netherlands, 9–12 July 2019. Available at: https://halshs.archives-ouvertes.fr/halshs-02179024 (Accessed: 12 July 2019).

Granovetter, M.S. (1973) 'The strength of weak ties', *American Journal of Sociology*, 78(6), pp. 1360–1380.

Granovetter, M.S. (1985) 'Economic action and social structure: The problem of embeddedness', *American Journal of Sociology*, 91(3), pp. 481–510.

Hachul, S. and Jünger, M. (2005) 'Drawing large graphs with a potential-field-based multilevel algorithm', in Pach, J. (ed.), *Graph Drawing. GD 2004. Lecture Notes in Computer Science*, vol. 3383. Berlin, Heidelberg: Springer, pp. 285–295. doi:10.1007/978-3-540-31843-9_29

Haraway, D. (1988) 'Situated knowledges: The science question in feminism and the privilege of partial perspective', *Feminist Studies*, 14(3), pp. 575–599.

Harel, D. and Koren, Y. (2000) 'A fast multi-scale method for drawing large graphs', in Marks, J. (ed.), *Graph Drawing. GD 2000. Lecture notes in computer science*, vol. 1984. Berlin, Heidelberg: Springer, pp. 183–196. doi: 10.1007/3-540-44541-2_18.

Henry, N. and Fekete., J.-D. (2007) 'Matlink: enhanced matrix visualization for analyzing social networks', in *INTERACT'07: Proceedings of the 11th IFIP TC 13 International Conference on Human-Computer Interaction*. Berlin, Heidelberg: Springer-Verlag, pp. 288–302.

Henry, N., Fekete, J.-D. and Mcguffin, M. (2012) 'NodeTrix: A hybrid visualization of social networks', *IEEE Transactions on Visualization and Computer Graphics*, vol. 13, no. 6, November–December 2007, pp. 1302–1309. doi:10.1109/TVCG.2007.70582.

Herman, I., Melançon, G. and Marshall, M.S. (2000) 'Graph visualization and navigation in information visualization: A survey', *IEEE Transactions on Visualization and Computer Graphics*, 6(1), pp. 24–43. doi:10.1109/2945.841119.

Hidalgo, C.A. (2016) 'Disconnected, fragmented, or united? A trans-disciplinary review of network science', *Applied Network Science*, 1(1), pp. 1–19. doi:10.1007/s41109-016-0010-3.

Hu, Y. and Shi, L. (2015) 'Visualizing large graphs', *Wiley Interdisciplinary Reviews: Computational Statistics*, 7(2), pp. 115–136. doi:10.1002/wics.1343.

Iliinsky, N. and Steele, J. (2011) *Designing data visualizations: Representing informational relationships*. Newton, MA: O'Reilly Media, Inc.

Ioannidis, J.P. (2005) 'Why most published research findings are false', *PLoS Medicine*, 2(8), e124.

Jacomy, M. (2020) 'Epistemic clashes in network science: Mapping the tensions between idiographic and nomothetic subcultures', *Big Data & Society*, 7(2). doi:10.1177/2053951720949577.

Jacomy, M., Venturini, T., Heymann, S. and Bastian, M. (2014) 'ForceAtlas2, a continuous graph layout algorithm for handy network visualization designed for the Gephi software', *PLoS ONE*, 9(6), pp. 1–18. doi:10.1371/journal.pone.0098679.

Jensen, T.E., Munk, A.K., Madsen, A.K. and Birkbak, A. (2014) 'Expanding the visual registers of STS', in Carusi, A., Hoel, A.S., Webmoor, T. and Woolgar, S. (eds.), *Visualization in the age of computerization*, pp. 226–230. doi:10.4324/9780203066973-11.

Jeong, H., Mason, S.P., Barabási, A.L. and Oltvai, Z.N. (2001) 'Lethality and centrality in protein networks', *Nature*, 411(6833), pp. 41-42.

Kamada, T. and Kawai, S. (1989) 'An algorithm for drawing general undirected graphs', *Information Processing Letters*, 31(1), pp. 7–15.

Kitchin, R. and Dodge, M. (2001) *Atlas of cyberspace*. San Francisco, CA: Addison-Wesley.

Kitchin, R. (2015) 'Big data and official statistics: Opportunities, challenges and risks', *Statistical Journal of the International Association of Official Statistics*, 31(3), pp. 471–481.

Kivelä, M., Arenas, A., Barthelemy, M., Gleeson, J.P., Moreno, Y. and Porter, M.A. (2014) 'Multilayer networks', *Journal of Complex Networks*, 2(3), pp. 203–271.

Knorr Cetina, K.D. (1999) *Epistemic cultures: How the sciences make knowledge*. Cambridge, MA: Harvard University Press.

Kobourov, S.G., McHedlidze, T. and Vonessen, L. (2015) 'Gestalt principles in graph drawing', in Di Giacomo, E. and Lubiw, A. (eds.), *Graph Drawing and Network Visualization. GD 2015. Lecture Notes in Computer Science*, vol. 9411, Berlin, Heidelberg: Springer. doi:10.1007/978-3-319-27261-0_50.

Kohonen, T. (1982) 'Self-organized formation of topologically correct feature maps', *Biological Cybernetics*, 43(1), pp. 59–69.

Kypridemou, E., Zito, M. and Bertamini, M. (2020) 'The effect of graph layout on the perception of graph properties', in *EUROVIS*. doi:10.2312/evs.20201039.

Krzywinski, M. (2011) 'Hive plots: rational network visualization – farewell to hairballs', *http://hiveplot.com* (Accessed: 09 December 2020).

Krzywinski, M., Birol, I., Jones, S.J. and Marra, M.A., (2012) 'Hive plots – rational approach to visualizing networks', *Briefings in Bioinformatics*, 13(5), pp. 627–644.

Labatut, V. and Orman, G.K. (2017) 'Community structure characterization', in Alhajj, R. and Rokne, J. (eds.), *Encyclopedia of social network analysis and mining*, pp. 1–13. doi:10.1007/978-1-4614-7163-9_110151-1.

Lambiotte, R., Delvenne, J.C. and Barahona, M. (2008) 'Laplacian dynamics and multiscale modular structure in networks', arXiv preprint arXiv:0812.1770.

Latour, B. (1986) 'Visualisation and cognition: Drawing things together', in Kucklick, H. (ed.), *Knowledge and society studies in the sociology of culture past and present*. Greenwich, CT: Jai Press, vol. 6, pp. 1–40.

Latour, B. (1994) 'On technical mediation', *Common Knowledge*, 3(2), pp. 29–64.

Latour, B. (1999) 'Circulating reference: Sampling the soil in the Amazon forest', in Latour, B., *Pandora's hope: Essays on the reality of science studies*, pp. 24–79.

Law, J. (2009) 'Collateral realities', version of 29th December 2009. Available at:

http://www.heterogeneities.net/publications/Law2009CollateralRealities.pdf (Accessed: 05 November 2020).

Lazega, E. and Snijders, T.A. (eds.) (2015) *Multilevel network analysis for the social sciences: Theory, methods and applications*. Berlin: Springer, vol. 12.

Lazer, D., Pentland, A., Adamic, L., Aral, S., Barabási, A.L., and Jebara, T. Brewer, D., Christakis, N., Contractor, N., Fowler, J., Gutmann, M., Jebara, T., King, G., Macy, M., Roy, D. and Van Alstyne, M. (2009) 'Computational social science', *Science*, 323(5915), pp. 721–723.

Lee, B., Plaisant, C., Parr, C.S., Fekete, J.-D. and Henry, N. (2006) 'Task taxonomy for graph visualization', in *Proceedings of the 2006 AVI Workshop on Beyond Time and Errors: Novel Evaluation Methods for Information Visualization*, Venice, Italy, May 2006, pp. 1–5.

Leskovec, J., Lang, K.J. and Mahoney, M. (2010) 'Empirical comparison of algorithms for network community detection', in *Proceedings of the 19th International Conference on World Wide Web – WWW '10*, Raleigh, North Carolina, USA, April 2010, pp. 631–640. doi:10.1145/1772690.1772755.

Lévy-Strauss, C. (1973) *Anthropologie structurale deux*. Paris: Plon, pp. 33-34.

Lima-Mendez, G. and Van Helden, J. (2009) 'The powerful law of the power law and other myths in network biology', *Molecular BioSystems* 5(12), pp. 1482–1493. Available at: https://pubs.rsc.org/en/content/articlehtml/2009/mb/b908681a (Accessed: 19 October 2020).

Madsen, A.K., Rison, J., Olesen, A.G., Thorsen, S., Spitzer, A., Schuff, S., Munk, A.K. and Guido, E. (2020) 'Do you live in a bubble?' Available at: https://tantlab.gehlpeople.com/ (Accessed: 09 December 2020).

Marres, N. (2012) 'On some uses and abuses of topology in the social analysis of technology (or the problem with smart meters)', *Theory, Culture & Society*, 29(5), pp. 288–310. doi:10.1177/0263276412454460.

Martin, S., Brown, W.M., Klavans, R. and Boyack, K.W. (2011) 'OpenOrd: An open-source toolbox for large graph layout', *Proceedings of SPIE, the International Society for Optical Engineering. Society of Photo-Optical Instrumentation Engineers*, San Francisco Airport, California, United States, 24 January 2011, vol. 7868. doi:10.1117/12.871402.

McGee, F., Ghoniem, M., Melançon, G., Otjacques, B. and Pinaud, B. (2019) 'The state of the art in multilayer network visualization', in *Computer Graphics Forum*, 38(6), pp. 125–149.

McGrath, C., Blythe, J. and Krackhardt, D. (1997) 'The effect of spatial arrangement on judgments and errors in interpreting graphs', *Social Networks*. Elsevier, 19(3), pp. 223–242. doi:10.1016/S0378-8733(96)00299-7.

Meidiana, A., Hong, S.H., Eades, P. and Keim, D. (2019) 'A quality metric for visualization of clusters in graphs', in Archambault, D. and Tóth, C. (eds.), *Graph Drawing and Network Visualization. GD 2019. Lecture Notes in Computer Science*, vol. 11904. Berlin, Heidelberg: Springer, pp. 125–138. doi:10.1007/978-3-030-35802-0_10.

Milgram, S. (1967) 'The small world problem', *Psychology Today*, 2(1), pp. 60–67.

Mol, A. (2006) 'Proving or improving: On health care research as a form of self-reflection', *Qualitative Health Research*, 16(3), pp. 405–414. doi:10.1177/1049732305285856.

Moreno, J.L. (1933) 'Emotions mapped by new geography', *New York Times*, 3, p. 17.

Moreno, J.L. (1934) *Nervous and mental disease monograph series, no 58. Who shall survive? A new approach to the problem of human interrelations*. Philadelphia, USA: Nervous and Mental Disease Publishing Co. doi:10.1037/10648-000.

Moreno, J.L. (1953) *Who shall survive? Foundations of sociometry, group psychotherapy and sociodrama*. Beacon, NY: Beacon House.

Munk, A.K. (20.18) 'Genanvendt: Et kritisk tilbageblik på digitale metoders konsekvenser for kontroverskortlægningen', *Dansk Sociologi*, 29(1), pp. 15–35.

Munk, A.K. (2019) 'Four styles of quali-quantitative analysis: Making sense of the new Nordic food movement on the web', *Nordicom Review*, 40(s1), pp. 159–176.

Munk, A.K. (2021) 'Tracing culinary discourse on Facebook: A digital methods approach', in Leer, J. and Krogager, S.G.S. (eds.), *Research Methods in Digital Food Studies*. Abingdon: Routledge.

Munk, A.K. and Olesen A. (2020) 'Beyond issue publics: Curating a corpus of generic Danish debate in the dying days of the Facebook API', *STS Encounters - DASTS Working Paper Series*, 11(1).

Munk, A.K., Madsen, A.K. and Jacomy, M. (2019) 'Thinking through the databody', in Mäkitalo , Å., Nicewonger , T.E. and Elam, M. (eds.), *Designs for Experimentation and Inquiry: Approaching Learning and Knowing in Digital Transformation*, p. 110.

Munzner, T. (2000) *Interactive visualization of large graphs and networks*, PhD thesis. Available at: papers2://publication/uuid/D241CECC-6C6B-46F5-87CA-1412547FF972 (Accessed: 12 October 2020).

Munzner, T. (2009) 'A nested model for visualization design and validation', in *IEEE Transactions on Visualization and Computer Graphics*, pp. 921–928. doi:10.1109/TVCG.2009.111.

Munzner, T. (2014) *Visualization analysis and design*. Boca Raton: CRC Press.

Newman, M.E. (2004) 'Fast algorithm for detecting community structure in networks', *Physical Review E*, 69(6), 066133.

Newman, M.E. (2018) *Networks*. Oxford: Oxford University Press.

Newman, M.E. and Girvan, M. (2004) 'Finding and evaluating community structure in networks', *Physical Review E*, 69(2), 026113.

Nguyen, Q.H., Eades, P. and Hong, S.-H. (2013) 'On the faithfulness of graph visualizations', in *IEEE Pacific Visualization Symposium*, pp. 209–216. doi:10.1109/PacificVis.2013.6596147.

Nguyen, Q.H., Eades, P. and Hong, S.-H. (2016) 'Towards faithful graph visualizations'. Available at: https://arxiv.org/pdf/1701.00921.pdf (Accessed: 01 July 2017).

Nick, B., Lee, C., Cunningham, P. and Brandes, U. (2013) 'Simmelian backbones: Amplifying hidden homophily in Facebook networks', in *Proceedings of the 2013 IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining, ASONAM 2013*, Niagara, Ontario, Canada, August 2013, pp. 525–532. doi:10.1145/2492517.2492569.

Noack, A. (2003) 'An energy model for visual graph clustering', in Liotta, G. (ed.), *Graph Drawing. GD 2003. Lecture Notes in Computer Science*, vol. 2912, Berlin, Heidelberg: Springer, pp. 425–436. doi:10.1007/978-3-540-24595-7_40.

Noack, A. (2007a) *Unified quality measures for clusterings, layouts, and orderings of graphs, and their application as software design criteria*, PhD thesis. Cottbus, Germany.

Noack, A. (2007b) 'Energy models for graph clustering', *Journal of Graph Algorithms and Applications JGAA*, 11(112), pp. 453–480.

Noack, A. (2009) 'Modularity clustering is force-directed layout', *Physical Review E – Statistical, Nonlinear, and Soft Matter Physics*, 79(2). doi:10.1103/PhysRevE.79.026102.

Nocaj, A., Ortmann, M. and Brandes, U. (2015) 'Untangling the hairballs of multi-centered, small-world online social media networks', *Journal of Graph Algorithms and Applications*, 19(2), pp. 595–618. doi:10.7155/jgaa.00370.

Olah, C., Mordvintsev, A. and Schubert, L. (2017) 'Feature visualization', *Distill, 2*(11), e7.

Peixoto, T.P. (2017) 'Bayesian stochastic blockmodeling', *arXiv* preprint arXiv:1705.10225.

Peixoto, T.P. (2019) 'Bayesian stochastic blockmodeling', in Doreian, P., Batagelj, V. and Ferligoj, A. (eds.) *Advances in network clustering and blockmodeling*, London: Wiley, pp. 289–332.

Peixoto, T.P. (2020) 'Revealing consensus and dissensus between network partitions', *arXiv* preprint arXiv:2005.13977.

Pewe, T.L. (1975) 'Quaternary geology of Alaska: U.S. Geological Survey', *Professional Paper*, 835, p. 145.

Purchase, H. (1997) 'Which aesthetic has the greatest effect on human understanding?', in Di Battista, G. (ed.), *Graph Drawing. GD 1997. Lecture Notes in Computer Science*, vol. 1353, Berlin, Heidelberg: Springer, pp. 248–261. doi:10.1007/3-540-63938-1_67.

Purchase, H.C. (2002) 'Metrics for graph drawing aesthetics', *Journal of Visual Languages and Computing*, 13(5), pp. 501–516. doi:10.1016/S1045-926X(02)90232-6.

Purchase, H.C., Cohen, R.F. and James, M. (1995) 'Validating graph drawing aesthetics', *Proceedings of Graph Drawing – Symposium on Graph Drawing, GD '95,* 1027, Passau, Germany, September 20–22, pp. 435–446. doi:10.1007/BFb0021827.

Rapoport, A. (1953) 'Spread of information through a population with socio-structural bias: I. Assumption of transitivity', *The Bulletin of Mathematical Biophysics, 15*(4), pp. 523–533.

Rieder, B. (2013) 'Studying Facebook via data extraction: The Netvizz application', in *Proceedings of the 5th Annual ACM Web Science Conference*, Paris, France, May 2013, pp. 346–355.

Rieder, B. (2020) *Engines of order: A mechanology of algorithmic techniques*. Amsterdam: Amsterdam University Press.

Rieder, B. and Röhle, T. (2017) 'Digital methods: From challenges to Bildung', in M.T. Schäfer & K. van Es (eds.), *The datafied society: Studying culture through data*. Amsterdam: Amsterdam University Press, pp. 109–124. doi:10.5117/9789462981362.

Rodrigues, E.M., Milic-Frayling, N., Smith, M., Shneiderman, B. and Hansen, D. (2011) 'Group-in-a-box layout for multi-faceted analysis of communities', *Third IEEE Conference on Social Computing 2011*, Boston, USA, 9–11 October 2011, pp. 354-361. doi:10.1109/PASSAT/SocialCom.2011.139.

Rogers, R. (2013) *Digital methods*. Boston, MA: MIT Press.

Roth, C. and Cointet, J.P. (2010) 'Social and semantic coevolution in knowledge networks', *Social Networks, 32*(1), pp. 16–29.

Ruppert, E. and Scheel, S. (2019) 'The politics of method: Taming the new, making data official', *International Political Sociology*, 13(3), pp. 233–252.

Shneiderman, B. and Dunne, C. (2013) 'Interactive network exploration to derive insights: Filtering, clustering, grouping, and simplification', in Didimo, W. and Patrignani, M. (eds.), *Graph Drawing. GD 2012. Lecture Notes in Computer Science*, vol. 7704, Berlin, Heidelberg: Springer, pp. 2–18. doi:10.1007/978-3-642-36763-2_2.

Sindre, G., Gulla, B. and Jokstad, H.G. (1993) 'Onion graphs: Aesthetics and layout', in *Proceedings – 1993 IEEE Symposium on Visual Languages, VL 1993*, Bergen, Norway, 24–27 August 1993. Institute of Electrical and Electronics Engineers Inc., pp. 287–291. doi:10.1109/VL.1993.269613.

Soni, U., Lu, Y., Hansen, B., Purchase, H.C., Kobourov, S. and Maciejewski, R. (2018) 'The perception of graph properties in graph layouts', *Computer Graphics Forum*, 37(3), pp. 169–181. doi:10.1111/cgf.13410.

Sugiyama, K. and Misue, K. (1995) 'Graph drawing by the magnetic spring model', *Journal of Visual Languages and Computing*, 6(3), pp. 217–231.

Sugiyama, K., Tagawa, S. and Toda, M. (1981) 'Methods for visual understanding of hierarchical system structures', *IEEE Transactions on Systems, Man and Cybernetics*, 11(2), pp. 109–125. doi:10.1109/TSMC.1981.4308636.

Sterne, J.A. and Smith, G.D. (2001) 'Sifting the evidence – what's wrong with significance tests?' *Physical Therapy*, 81(8), pp. 1464–1469.

Tamassia, R., Di Battista, G. and Batini, C. (1988) 'Automatic graph drawing and readability of diagrams', *IEEE Transactions on Systems, Man and Cybernetics*, 18(1), pp. 61–79. doi:10.1109/21.87055.

Theocharis, Y. and Jungherr, A. (2020) 'Computational social science and the study of political communication', *Political Communication*, pp. 1–22. doi:10.1080/10584609.2020.1833121

Traag, V.A., Waltman, L. and van Eck, N.J. (2019) 'From Louvain to Leiden: Guaranteeing well-connected communities', *Scientific Reports*, 9(1), pp. 1–12.

Tufte, E.R. (1983) *The visual display of quantitative information.* Cheshire, CT: Graphics Press.

Tukey, J.W. (1977) *Exploratory data analysis*, Boston, MA: Addison-Wesley, vol. 2, pp. 131–160.

Tukey, J.W. (1962) 'The future of data analysis', *The Annals of Mathematical Statistics*, 33(1), pp. 1–67.

Tutte, W.T. (1963) 'How to draw a graph', *Proceedings of the London Mathematical Society*, 3(1), pp. 743–767.

Van Den Elzen, S. and Van Wijk, J.J. (2014) 'Multivariate network exploration and presentation: From detail to overview via selections and aggregations', *IEEE Transactions on Visualization and Computer Graphics*, 20(12), pp. 2310–2319. doi:10.1109/TVCG.2014.2346441.

Van Geenen, D. (2020) 'The role of software tools in critical data studies practices. Studying the affordances of Gephi as a sociotechnical system', in Burkhardt, M., Grashöfer, K., Shnayien, M. and Westermann, B. (eds), *Explorations in digital cultures: On the politics of datafication, calculation and networking*. Lüneburg: Meson Press.

Van Ham, F. and Rogowitz, B.E. (2008) 'Perceptual organization in user-generated graph layouts', in *IEEE Transactions on Visualization and Computer Graphics*, pp. 1333–1339. doi:10.1109/TVCG.2008.155.

Vehlow, C., Beck, F. and Weiskopf, D. (2015) 'The state of the art in visualizing group structures in graphs', in Borgo, R., Ganovelli, F., and Viola, I. (eds), *Eurovis: Eurographics/ IEEE Symposium on Visualization*, pp. 21–40. doi:10.2312/eurovisstar.20151110.

Venturini, T., Jacomy, M., Bounegru, L. and Gray, J. (2018) 'Visual network exploration for data journalists', in Franklin, S.E.I. and B. (ed.), *The Routledge handbook to developments in digital journalism Studies*. Abingdon: Routledge.

Venturini, T., Jacomy, M. and Pereira, D. (2014) 'Visual network analysis', Sciences Po médialab. Available at: http://www.tommasoventurini.it/wp/wp-content/uploads/2014/08/Venturini-Jacomy_Visual-Network-Analysis_WorkingPaper.pdf (Accessed: 10 October 2020).

Venturini, T. and Munk, A.K. (2021) *Controversy mapping: A field guide*. Cambridge, MA: Polity Press.

Venturini, T., Munk, A.K. and Jacomy, M. (2019) 'Actor-network vs network analysis vs digital networks: Are we talking about the same networks?', in Vertesi, J. and Ribes, D. (eds.), *DigitalSTS: A handbook and fieldguide*. Princeton, NJ: Princeton University Press, pp. 510–524. Available at: https://digitalsts.net/wp-content/uploads/2019/11/32_digitalSTS_Actor-Network.pdf (Accessed: 02 September 2020).

Von Landesberger, T., Kuijper, A., Schreck, T., Kohlhammer, J. van Wijk, J.J., Fekete, J.-D. and Fellner, D.W. (2011) 'Visual analysis of large graphs: State-of-the-art and future research challenges', *Computer Graphics Forum*, 30(6), pp. 1719–1749. doi:10.1111/j.1467-8659.2011.01898.x.

Wagemans, J., Elder, J.H., Kubovy, M., Palmer, S.E., Peterson, M.A., Singh, M. and von der Heydt, R. (2012) 'A century of Gestalt psychology in visual perception: I. Perceptual grouping and figure–ground organization', *Psychological Bulletin*, 138(6), 1172-217. doi:10.1037/a0029333.

Watts, D. and Strogatz, S. (1998) 'Collective dynamics of "smallworld" networks', *Nature*, 393, pp. 440–442.

White, H. (1963) *An anatomy of kinship: Mathematical models for structures of cumulated roles*. Engelwood, NJ: Prentice Hall.

Wieringa, M.A., van Geenen, D., van Es, K.F. and van Nuss, J. (2019) 'The fieldnotes plugin: Making network visualization in Gephi accountable', *Good Data*, 29, pp. 277–296.

Yang, J. and Leskovec, J. (2014) 'Overlapping communities explain core-periphery organization of networks', *Proceedings of the IEEE*, 102(12), pp. 1892–1902. doi:10.1109/JPROC.2014.2364018.

Yazdani, A. and Jeffrey, P. (2011) 'Complex network analysis of water distribution systems', *Chaos: An Interdisciplinary Journal of Nonlinear Science*, 21(1), 016111.

Yin, H., Benson, A.R. and Ugander, J. (2020) 'Measuring directed triadic closure with closure coefficients', *Network Science*, 8(4), pp. 551–573. doi:10.1017/nws.2020.20.

Yosinski, J., Clune, J., Nguyen, A., Fuchs, T. and Lipson, H. (2015) 'Understanding neural networks through deep visualization', *arXiv* preprint arXiv:1506.06579.

APPENDIX A. GEPHI

This two-pager was published in the *Proceedings of the International Conference on Web and Social Media* (ICWSM) 2009. This is generally cited when researchers use Gephi (6,100 times according to Google Scholar, 21 August 2020). It was awarded the Test of Time Award at ICWSM 2019.

Bastian, M., Heymann, S. and Jacomy, M. (2009) 'Gephi: An open source software for exploring and manipulating networks', in *Third International ICWSM Conference*, pp. 361–362. Available at: http://www.aaai.org/ocs/index.php/ICWSM/09/paper/viewFile/154/1009/ (Accessed: 13 March 2017).

Gephi: An Open Source Software for Exploring and Manipulating Networks

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Abstract

Gephi is an open source software for graph and network analysis. It uses a 3D render engine to display large networks in real-time and to speed up the exploration. A flexible and multi-task architecture brings new possibilities to work with complex data sets and produce valuable visual results. We present several key features of Gephi in the context of interactive exploration and interpretation of networks. It provides easy and broad access to network data and allows for spatializing, filtering, navigating, manipulating and clustering. Finally, by presenting dynamic features of Gephi, we highlight key aspects of dynamic network visualization.

Visualization and Exploration of Large Graphs

In the aim of understanding networks, the visualization of large graphs has been developed for many years in many successful projects (Batagelj 1998; Shannon 2003; Adar 2006). Visualizations are useful to leverage the perceptual abilities of humans to find features in network structure and data. However this process is inherently difficult and requires exploration strategy (Perer 2006). As well as being technically accurate and visually attractive, network exploration tools must head toward real-time visualizations and analysis to improve the user's exploratory process. Interactive techniques have successfully guided domain experts through the complex exploration of large networks.

We can identify some main requirements for a network exploration tool: high quality layout algorithms, data filtering, clustering, statistics and annotation. In practice these requirements must be included in a flexible, scalable and user-friendly software. Focusing on analysis clarity and on modern user interface, the Gephi project brings better network visualization to both experts and uninitiated audience. Inspired by WYSIWYG editors like Adobe Photoshop, we develop modules set around a center visualization window.

The Gephi Software

Gephi is an open source network exploration and manipulation software. Developed modules can import, visualize, spatialize, filter, manipulate and export all types of networks. The visualization module uses a special 3D render engine to render graphs in real-time. This technique uses the computer graphic card, as video games do, and leaves the CPU free for other computing. It can deal with large network (i.e. over 20,000 nodes) and, because it is built on a multi-task model, it takes advantage of multi-core processors. Node design can be personalized, instead of a classical shape it can be a texture, a panel or a photo. Highly configurable layout algorithms can be run in real-time on the graph window. For instance speed, gravity, repulsion, auto-stabilize, inertia or size-adjust are real-time settings of the *Force Atlas* algorithm, a special force-directed algorithm developed by our team. Several algorithms can be run in the same time, in separate workspaces without blocking the user interface. The text module can show labels on the visualization window from any data attribute associated to nodes. A special algorithm named *Label Adjust* can be run to avoid label overlapping (Figure 1).

Figure 1: Label Adjust algorithm avoid label overlapping

The user interface (Figure 2) is structured into Workspaces, where separate work can be done, and a powerful plugin system is currently developed. Great attention has been taken to the extensibility of the software. An algorithm, filter or tool can be easily added to the program, with little programming experience. Sets of nodes or edges can be obtained manually or by using the filter system. Filters can select nodes or edges with thresholds, range and other properties. In practice filter boxes are chained, each box take in input the output of the upper box. Thus, it is easy to divide a bi-partite network or to get the nodes that have an in-degree superior to 5 and the property "type" set to "1". Because the usefulness of a network analysis often comes from the data associated to nodes/edges, ordering and clustering can be processed according to these values. With

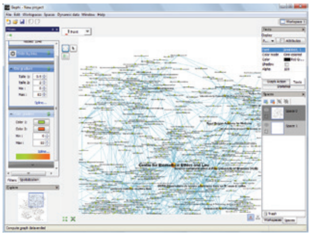

Figure 2: A screenshot of Gephi beta version 0.6

sets of nodes, graphical modules like *Size Gradient*, *Color Gradient* or *Color clusters* can then be applied to change the network design. Graphical modules take a set of nodes in input and modify the display parameters, like colors or size, to corroborate understanding of the network structure or content.

Though networks can be explored in an interactive way with the visualization module, it can also be exported as a SVG or PDF file. The vectorial files can then be shared or printed. A powerful SVG exporter named *Rich SVG Export* is included in Gephi. Many options are offered to users to set the design of nodes, edges and labels. Techniques are developed to increase networks clarity and readability. Special care is taken about fonts and labels. For instance, small labels can be drawn on edges to immediately see the neighbours of a node. The Figure 3 shows the brain network of the C. Elegans worm (Watts 1998) exported from Gephi.

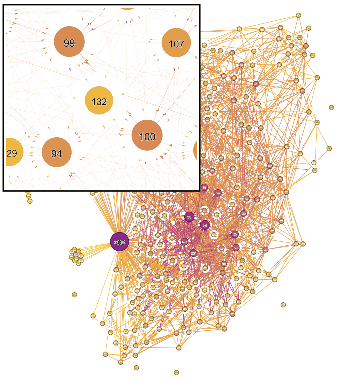

Figure 3: SVG File exported from Gephi

The current studies of network dynamics has brought some very interesting case study. Dynamic network visualization offer possibilities to understand structure transition or content propagation (Moody 2005). Exploring dynamic networks in an easy and intuitive way has been incorporated in Gephi from the beginning. The architecture supports graphs whose structure or content varies over time, and propose a timeline component where a slice of the network can be retrieved. From the time range of the timeline slice, the system queries all nodes and edges that match and update the visualization module. Hence a dynamic network can be played as movie sequences.

The dynamic module can get network data from either a compatible graph file or from external data sources. When running, a data source can send network data to the dynamic controller at any time and immediately see the results on the visualization module. For instance a web-crawler can be connected to Gephi in order to see the network construction over time. The architecture is interoperable and data source can be created easily to communicate with existing software, third parties databases or web-services.

Future work

Though the core of the software already exists, further work is required for the development of new features, especially filters, statitics and tools. A special focus is made on clustering and hierarchical networks. Improvements will be integrated to the data structure to support grouping and navigation within a network hierarchy. As for spatialization algorithms, a framework will be able to host various classification algorithms.

As we continue to receive feedbacks, we are looking forward to better adapt the user interface to users' need. Gephi has been successfully used for Internet link and semantic network case studies. It is also frequently used for SNA. An effort has been made to speed up the analysis process, from data import to map export. Gephi is developed toward supporting the whole process with only user interface manipulation. The developement of dynamic features are also one of the top priorities.

Availability

Gephi is available at http://gephi.org

References

Adar, E. 2006. Guess: a language and interface for graph exploration. In *CHI '06: Proceedings of the SIGCHI conference on Human Factors in computing systems*, 791–800.

Batagelj, M. 1998. Pajek - program for large network analysis. *Connections* 21:47–57.

Moody, McFarland, B.-d. 2005. Dynamic network visualization. *American Journal of Sociology* 110(4):1206–1241.

Perer, S. 2006. Balancing systematic and flexible exploration of social networks. *Visualization and Computer Graphics, IEEE Transactions on* 12(5):693–700.

Shannon, Markiel, O. e. a. 2003. Cytoscape: a software environment for integrated models of biomolecular interaction networks. *Genome Res* 13(11):2498–2504.

Watts, S. 1998. Collective dynamics of 'small-world' networks. *Nature* 393(6684):440–442.

APPENDIX B. FORCE ATLAS 2

Published in *PLoS ONE*. It is often cited when researchers use the Force Atlas 2 algorithm (1,300 times according to Google Scholar, 21 August 2020).

Jacomy, M., Venturini, T., Heymann, S. and Bastian, M. (2014) 'ForceAtlas2, a continuous graph layout algorithm for handy network visualization designed for the Gephi software', *PLOS ONE*, 9(6), pp. 1–18. doi:10.1371/journal.pone.0098679.

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ForceAtlas2, a Continuous Graph Layout Algorithm for Handy Network Visualization Designed for the Gephi Software

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Abstract

Gephi is a network visualization software used in various disciplines (social network analysis, biology, genomics…). One of its key features is the ability to display the spatialization process, aiming at transforming the network into a map, and ForceAtlas2 is its default layout algorithm. The latter is developed by the Gephi team as an all-around solution to Gephi users' typical networks (scale-free, 10 to 10,000 nodes). We present here for the first time its functioning and settings. ForceAtlas2 is a force-directed layout close to other algorithms used for network spatialization. We do not claim a theoretical advance but an attempt to integrate different techniques such as the Barnes Hut simulation, degree-dependent repulsive force, and local and global adaptive temperatures. It is designed for the Gephi user experience (it is a continuous algorithm), and we explain which constraints it implies. The algorithm benefits from much feedback and is developed in order to provide many possibilities through its settings. We lay out its complete functioning for the users who need a precise understanding of its behaviour, from the formulas to graphic illustration of the result. We propose a benchmark for our compromise between performance and quality. We also explain why we integrated its various features and discuss our design choices.

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Introduction

This paper addresses two different audiences. To Gephi users, we offer a complete description of the ForceAtlas2 algorithm and its settings. To the researchers or engineers interested in the development of spatialization algorithms, we offer a discussion of our choices of features and implementation.

If developing an algorithm is "research" and implementing it is "engineering", then a specificity of Gephi overall, is that it is based in engineering rather than in research. This is why it looks so different to a software like Pajek. This is also why ForceAtlas2 is more about usability than originality.

Our contribution to the mathematics of network spatialization is limited to the benchmark of a specific implementation of adaptive speed (step length selection). This paper focuses more on how classical techniques fit together in the perspective of a rich user experience - and which techniques do not.

It is necessary to explain quickly how the user feedback led us to the specific orientation of ForceAtlas2 (a continuous algorithm). In the next sections we will explore the different techniques gathered in this layout, with some formal terminology and many illustrations. We will discuss our implementation of step length selection with examples and a benchmark. And finally we will offer a short discussion about the general design of the algorithm.

In 2008 we started to develop Gephi [1], a software to visualize and manipulate networks, at the Maison des Sciences de l'Homme in Paris under the direction of Dana Diminescu [2]. Our goal was to provide some network analysis methods to social scientists, that would not require learning graph theory.

Three reference softwares inspired us: Pajek [3], GUESS [4] and TouchGraph. TouchGraph offered a manipulative interface that we highly appreciated, but it had serious performance issues and the layout was not adapted to scale-free networks of a hundred nodes or more (high visual cluttering). Pajek is very powerful but not adapted to dynamic exploration (it is designed as a computation software, where visualization is a bonus). GUESS was the most adapted to our needs, being user-centric and implementing state-of-the-art spatialization algorithms such as GEM [5].

We do not explore here the reasons why we created Gephi rather than just using GUESS, since it is a much larger discussion. However, an important point for this paper is that we wanted a *continuous* layout, that runs homogeneously and which can be displayed. Visualizing the "live" spatialization is a key feature of Gephi. It provides a very intuitive understanding of the layout process and its settings. It allows users to have a trial-error approach to the layout, that improves the learning curve of Gephi.

We developed ForceAtlas2 by combining existing techniques. We did it "wildly": we did not start from a systematic review of academic papers, and we eventually redeveloped existing techniques. We implemented features when they were needed by users, and we tried to incorporate user-friendly settings in the design. (When we reworked all the settings, we created a "version 2" of "ForceAtlas" to avoid a too confusing change. Both versions are still available in Gephi even if the first version is obsolete.) We focused ForceAtlas2 on fluency and quality, because fluency is required by Gephi's interactive user experience, and because researchers prefer quality over performance.

The fundamentals of the algorithm are not sophisticated. As long as it runs, the nodes repulse and the edges attract. This push for simplicity comes from a need for transparency. Social scientists cannot use black boxes, because any processing has to be evaluated in the perspective of the methodology. Our features change the forces or how they are simulated, but keep this model of continuous force directed layout: forces apply continuously as long as the layout is running. We give more details about our reasons at this end of this paper.

Developing a continuous algorithm prevented us from implementing many powerful techniques. We cite here some techniques that we intentionally avoided for focusing reasons. Simulated annealing [6] cannot be fully implemented, nor can any auto-stop feature (like Yifan Hu [7], also implemented in Gephi). Our layout stops exclusively at the user's request. Phased strategies, used for example by OpenOrd [8], are by definition incompatible, even if in this case it allows OpenOrd to spatialize much larger networks. Graph coarsening [7,9] cannot be implemented for the same reason. Finally, strategies where forces do not apply homogeneously do not necessary fit, because the motion of the network during the layout is not as fluid and it impacts the user experience. It is especially the case of the old Kamada Kawai [10] and more recently GEM [5].

We abandoned many techniques by keeping ForceAtlas2 continuous. But most of these are actually optimizations, and our performances are still compatible with the size of networks managed by Gephi (as we will see). We were able to implement qualitative features that impact the placement of the nodes, such as a degree-dependent repulsion force suggested by Noack [11], gravitation, and other features. We also implemented the Lin-Log forces proposed by Noack, a great inspiration for us, since his conception of layout quality corresponds to researchers' needs (a visual interpretation of modularity).

Anatomy of ForceAtlas2

ForceAtlas2 is a force directed layout: it simulates a physical system in order to spatialize a network. Nodes repulse each other like charged particles, while edges attract their nodes, like springs. These forces create a movement that converges to a balanced state. This final configuration is expected to help the interpretation of the data.

The force-directed drawing has the specificity of placing each node depending on the other nodes. This process depends only on the connections between nodes. Eventual attributes of nodes are never taken into account. This strategy has its drawbacks. The result varies depending on the initial state. The process can get stuck in a local minimum. It is not deterministic, and the coordinates of each point do not reflect any specific variable. The result cannot be read as a Cartesian projection. The position of a node cannot be interpreted on its own, it has to be compared to the others. Despite these issues, the technique has the advantage of allowing a visual interpretation of the structure. Its very essence is to turn structural proximities into visual proximities, facilitating the analysis and in particular the analysis of social networks. Noack [12] has shown that the proximities express communities. Noack relies on the very intuitive approach of Newman [13,14]: actors have more relations inside their community than outside, communities are groups with denser relations. Newman proposes an unbiased measure of this type of collective proximity, called "modularity". Noack [12] has shown that force-directed layouts optimize this measure: communities appear as groups of nodes. Force-directed layouts produce visual densities that denote structural densities. Other types of layouts allow a visual interpretation of the structure, like the deterministic layout "Hive Plots" [15], but they do not depict the modular aspect of the structure.

Energy Model

Every force-directed algorithm relies on a certain formula for the attraction force and a certain formula for the repulsion force. The "spring-electric" layout [16] is a simulation inspired by real life. It uses the repulsion formula of electrically charged particles ($F_r = k/d^2$) and the attraction formula of springs ($F_a = -k \cdot d$) involving the geometric distance d between two nodes. Fruchterman and Rheingold [17] created an efficient algorithm using custom forces (attraction $F_a = d^2/k$ and repulsion $F_r = -k^2/d$, with k adjusting the scaling of the network). Note that actually, non-realistic forces have been used since the beginning, noticeably by Eades [16] in his pioneer algorithm. Fruchterman and Rheingold were inspired by Eades' work, and they noticed that despite using the spring metaphor to explain his algorithm, the attraction force is not that of a spring.

Sixteen years later, Noack [11] explained that the most important difference among force-directed algorithms is the role played by distance in graph spatialization. In physical systems, forces depend on the distance between the interacting entities:

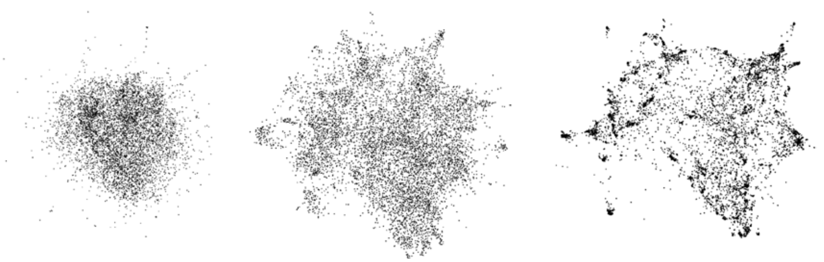


Figure 1. Layouts with different types of forces. Layouts with Fruchterman-Reingold ($a-r=3$), ForceAtlas2 ($a-r=2$) and the LinLog mode of ForceAtlas2 ($a-r=1$).
doi:10.1371/journal.pone.0098679.g001

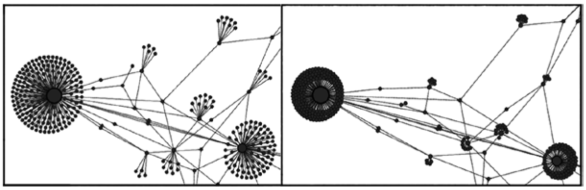


Figure 2. Regular repulsion vs. repulsion by degree. Fruchterman-Rheingold layout on the left (regular repulsion) and ForceAtlas2 on the right (repulsion by degree). While the global scheme remains, poorly connected nodes are closer to highly connected nodes. ($a-r=1$).
doi:10.1371/journal.pone.0098679.g002

closer entities attract less and repulse more than more distant entities and vice versa. The interdependence between distance and forces can be linear, exponential or logarithmic. The spring model for example, replicates precisely the physical forces from which it is inspired, thereby establishing a linear proportionality between the distance and the force (as for the spring attraction) and as a square proportionality between the distance and the force, as for electromagnetic repulsion. Noack defines the energy model or "(attraction,repulsion)-model" of a layout as the exponent taken by distance in the formulas used to calculate attraction and repulsion (the *log* being considered as the 0^{th} power). For example, the model of the spring-electric layout is $(1,-2)$.

The (attraction,repulsion)-model of ForceAtlas $(1,-1)$ has an intermediate position between Noack's LinLog $(0,-1)$ and the algorithm of Fruchterman and Rheingold $(2,-1)$, as pictured in Figure 1.

Noack [12] states that "distances are less dependent on densities for large $a-r$, and less dependent on path lengths for small a" (the "density" is the ratio of actual edges on potential edges). It means that visual clusters denote structural densities when $a-r$ is low, that is when the attraction force depends less on distance, and when the repulsion force depends more on it. ForceAtlas2's ability to show clusters is better than Fruchterman and Rheingold's algorithm but not as good as the LinLog (Figure 1).

A classical attraction force. The attraction force F_a between two connected nodes n_1 and n_2 is nothing remarkable. It depends linearly on the distance $d(n_1,n_2)$. We will explain later why there is no constant adjusting of this force.

$$F_a(n_1,n_2)=d(n_1,n_2) \tag{1}$$

Repulsion by degree. A typical use case of ForceAtlas2 is the social network. A common feature of this type of network is the presence of many "leaves" (nodes that have only one neighbor).

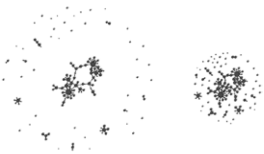


Figure 3. Effects of the gravity. ForceAtlas2 with gravity at 2 and 5. Gravity brings disconnected components closer to the center (and slightly affects the shape of the components as a side-effect).
doi:10.1371/journal.pone.0098679.g003

This is due to the power-law distribution of degrees that characterizes many real-world data. The forests of "leaves" surrounding the few highly connected nodes is one of the principal sources of visual cluttering. We take into account the degree of the nodes (the count of connected edges) in the repulsion, so that this specific visual cluttering is reduced.

The idea is to bring poorly connected nodes closer to very connected nodes. Our solution is to tweak the repulsion force so that it is weaker between a very connected node and a poorly connected one. As a consequence they will end up being closer in the balanced state (Figure 2). Our repulsion force F_r is proportional to the produce of the degrees plus one ($deg+1$) of the two nodes. The coefficient k_r is defined by the settings.

$$F_r(n_1,n_2)=k_r\frac{(deg(n_1)+1)(deg(n_2)+1)}{d(n_1,n_2)} \tag{2}$$

This formula is very similar to the edge repulsion proposed by Noack [11] except that he uses degree and not the degree plus one. The $+1$ is important as it ensures that even nodes with a degree of zero still have some repulsion force. We speculate that this feature has more impact on the result and its readability than the (attraction, repulsion)-model.

Settings

We detail now the settings proposed to the user, what they implement, and their impact on the layout. Most of these settings allow the user to affect the placement of nodes (the shape of the network). They allow the user to get a new perspective on the data and/or to solve a specific problem. They can be activated while the layout is running, thus allowing the user to see how they impact the spatialization.

LinLog mode. Andreas Noack produced an excellent work on placement quality measures [18]. His LinLog energy model arguably provides the most readable placements, since it results in a placement that corresponds to Newman's modularity [14], a widely used measure of community structure. The LinLog mode just uses a logarithmic attraction force.

$$F_a(n_1,n_2)=log(1+d(n_1,n_2)) \tag{3}$$

This formula is different from Noack's since we add 1 to the distance to manage superposed nodes ($log(0)$ would produce an error). We have already seen that this energy model has a strong impact on the shape of the graph, making the clusters tighter (Figure 1). We also observed that it converges slowly in some cases.

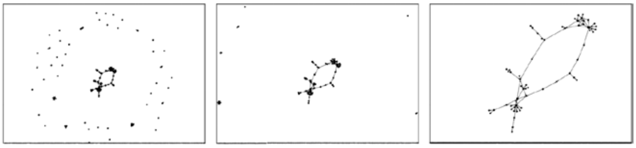


Figure 4. Effects of the scaling. ForceAtlas2 with scaling at 1, 2 and 10. The whole graph expands as scaling affects the distance between components as well as their size. Note that the size of the nodes remains the same; scaling is not zooming.
doi:10.1371/journal.pone.0098679.g004

Switching from regular mode to LinLog mode needs a readjustment of the scaling parameter.

Gravity. Gravity is a common improvement of force-directed layouts. This force $F_g(n)$ prevents disconnected components (islands) from drifting away, as pictured in Figure 3. It attracts nodes to the center of the spatialization space. Its main purpose is to compensate repulsion for nodes that are far away from the center. In our case it needs to be weighted like the repulsion:

$$F_g(n) = k_g(deg(n)+1) \tag{4}$$

k_g is set by the user.

The "Strong gravity" option sets a force that attracts the nodes that are distant from the center more ($d(n)$ is this distance). This force has the drawback of being so strong that it is sometimes stronger than the other forces. It may result in a biased placement of the nodes. However, its advantage is to force a very compact layout, which may be useful for certain purposes.

$$F'_g(n) = k_g(deg(n)+1)d(n) \tag{5}$$

Scaling. A force-directed layout may contain a couple of constants k_a and k_r playing an opposite role in the spatialization of the graph. The attraction constant k_a adjusts the attraction force, and k_r the repulsion force. Increasing k_a reduces the size of the graph while increasing k_r expands it. In the first version of ForceAtlas, the user could modify the value of both variables. For practical purposes, however, it is better to have only one single scaling parameter. In ForceAtlas2, the scaling is k_r while there is no k_a. The higher k_r, the larger the graph will be, as you can see in Figure 4.

Edge weight. If the edges are weighted, this weight will be taken into consideration in the computation of the attraction force. This can have a dramatic impact on the result, as pictured in Figure 5. If the setting "Edge Weight Influence" δ is set to 0, the weights are ignored. If it is set to 1, then the attraction is proportional to the weight. Values above 1 emphasize the weight effects. This parameter is used to modify the attraction force according to the weight $w(e)$ of the edge e:

$$F_a = w(e)^{\delta} d(n_1,n_2) \tag{6}$$

Dissuade Hubs. ForceAtlas2 has a "Dissuade Hubs" mode that, once activated, affects the shape of the graph by dividing the attraction force of each node by its degree plus 1 for nodes it points to. When active, the attraction force is computed as follows:

$$F_a(n_1,n_2) = \frac{d(n_1,n_2)}{deg(n_1)+1} \tag{7}$$

This mode is meant to grant authorities (nodes with a high indegree) a more central position than hubs (nodes with a high outdegree). This is useful for social networks and web networks, where authorities are sometimes considered more important than hubs. "Dissuade Hubs" tends to push hubs to the periphery while keeping authorities in the center. Note that here we improperly use the concepts of Hub and Authority defined by Kleinberg [19]. We do not actually compute the HITS algorithm for performance issues.

Prevent Overlapping. With this mode enabled, the repulsion is modified so that the nodes do not overlap. The goal is to produce a more readable and aesthetically pleasing image, as pictured in Figure 6.

The idea is to take into account the size of the nodes $size(n)$ in computing the distance $d(n_1,n_2)$ both in the attraction force and in the repulsion force.

- $d'(n_1,n_2) = d(n_1,n_2) - size(n_1) - size(n_2)$ is the "border-to-border" distance preventing overlapping.
- if $d'(n_1,n_2) > 0$ (no overlapping) then we use d' instead of d to compute forces:

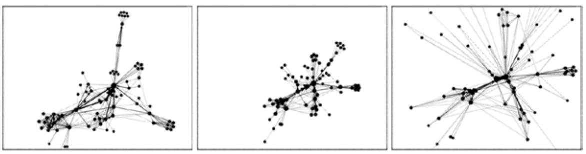


Figure 5. Effects of the edge weight influence. ForceAtlas2 with Edge Weight Influence at 0, 1 and 2 on a graph with weighted edges. It has a strong impact on the shape of the network.
doi:10.1371/journal.pone.0098679.g005

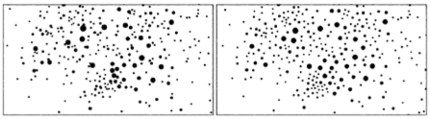


Figure 6. Effects of the overlapping prevention. ForceAtlas2 without and with the nodes overlapping prevention.
doi:10.1371/journal.pone.0098679.g006

$$F_a(n_1,n_2) = d'(n_1,n_2)$$

$$F_r(n_1,n_2) = k_r \frac{(deg(n_1)+1)(deg(n_2)+1)}{d'(n_1,n_2)}$$

- if $d'(n_1,n_2) < 0$ (overlapping) then no attraction and a stronger repulsion:

$$F_a(n_1,n_2) = 0$$

$$F_r(n_1,n_2) = k'_r(deg(n_1)+1)(deg(n_2)+1)$$

- if $d'(n_1,n_2) = 0$ then there is no attraction and no repulsion

In Gephi's implementation k'_r is arbitrarily set to 100. Note that the swinging measure is biased due to this option, that is why we also implemented a diminishing factor on the local speed (dividing it by 10). It is important to notice that this mode adds a considerable friction in the convergence movement, slowing spatialization performances. It is necessary to apply it only after the convergence of graph spatialization.

Approximate repulsion. In order to improve spatialization performances on big graphs, we implemented the optimization of Barnes Hut [20]. Relying on an approximate computation of repulsion forces, such optimization generates approximation and may be counter-productive on small networks, thus we allow the user to disable it. Besides from the side effects of the approximation, it does not impact the shape of the layout. Without the Barnes Hut optimization, the complexity time is $O(n^2)$ where n is the number of nodes.

Performance Optimization

The Issue of Speed

When employing a force-based layout, users have to deal with a speed/precision trade-off. Speed may accelerate the convergence, but the lack of precision may prevent it. This issue is a consequence of using a simulation of the forces. It appears in any force-directed algorithm as well as in other types of simulations. The time is not something continuous in the simulation, because it is computed step-by-step. When using many computing steps, a precise simulation is produced but it takes longer to compute: it is slow. If few steps are chosen, it is computed quickly but the simulation is imprecise. Reducing the number of steps is making a rougher approximation of the system. The proper term to discuss this would be ''step length'', since it is the mathematical variable that we actually use. But we will prefer here the term of ''speed'', because it is closer to the experience of users. The speed of the simulation is just like the step length: a high speed means long steps (less precision), a low speed means short steps (more precision). In a force-directed algorithm, increasing the speed makes the precision drop. We cannot have speed and precision at the same time. The effect of the approximation is that some nodes become unable to find a stable position and start oscillating around their balancing position (Figure 7).

This oscillation problem is known as a problem of ''temperature'', because we can compare the movement of a node to the temperature of a molecule. Different solutions exist: local temperatures as featured in GEM [5], adaptive cooling as featured in Yifan Hu [7] or simulated annealing [6]. ForceAtlas2 features its own implementation of local temperatures as well as adaptive cooling, but in the perspective of a continuous layout. In terms of ''speed vs. precision'', since users are more comfortable with these concepts, we compute an optimal speed for each node as well as for the whole graph. Our strategy is to measure oscillations and to compute a speed that allows only a certain amount of oscillation. This amount is set by the user as ''Tolerance (speed)''. In Gephi's implementation, we set three default values: 0.1 under 5000 nodes, 1 up to 50000 nodes and 10 above 50000. We now describe how this feature works.

Adapting the Local Speed

We implemented a strategy aimed at optimizing the convergence. Researchers often visualize scale-free networks where some

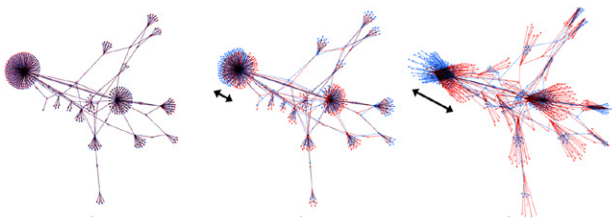


Figure 7. The oscillation of nodes increases with speed. Fruchterman-Rheingold layout at speeds 100, 500 and 2,500 (superposition at two successive steps).
doi:10.1371/journal.pone.0098679.g007

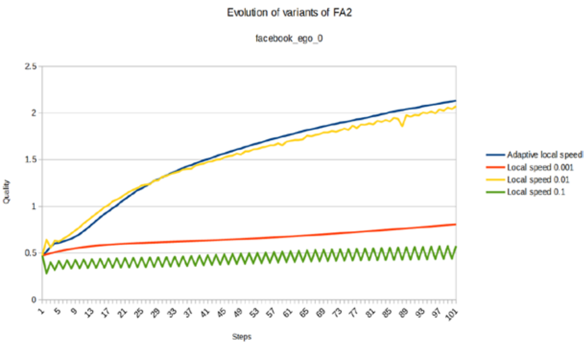


Figure 8. Adaptive local speed is a good compromise. Evolution of the quality of ForceAtlas2 variants at each iteration (the higher the better). Different values of the local speed give different behaviors. The adaptive local speed achieves the best compromise between performance and quality. The network used is ''facebook_ego_0'' from our dataset.
doi:10.1371/journal.pone.0098679.g008

nodes gather a huge amount of edges. Highly connected nodes have a high temperature. They tend to oscillate quickly, and require a high level of precision, thus a low speed. Poorly connected nodes are very stable and so can operate at high speed. If we have different speeds for different nodes, we can achieve a much better performance. Our strategy is to determine the speed of each node by observing its oscillation, like in GEM [5]. But our implementation is actually quite different.

Our version of oscillation is based on the forces applied to each node, and we call it ''swinging'' (oscillation is about distances). We

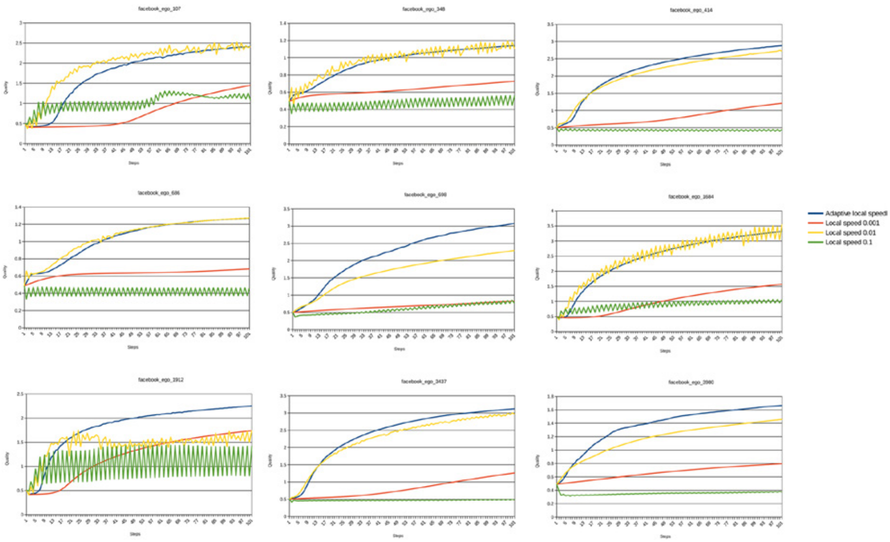


Figure 9. Effects of adaptive local speed on different networks. Evolution of the quality of ForceAtlas2 variants at each iteration on the other facebook ego-networks of our dataset. The adaptive local speed is always the best. Local speed 0.001 converges poorly because the speed is too low. Local speed 0.1 converges poorly because it oscillates a lot: the speed is too high. Local speed 0.01 is sometimes adapted to the network, and sometimes not, but never outperforms the adaptive speed.
doi:10.1371/journal.pone.0098679.g009

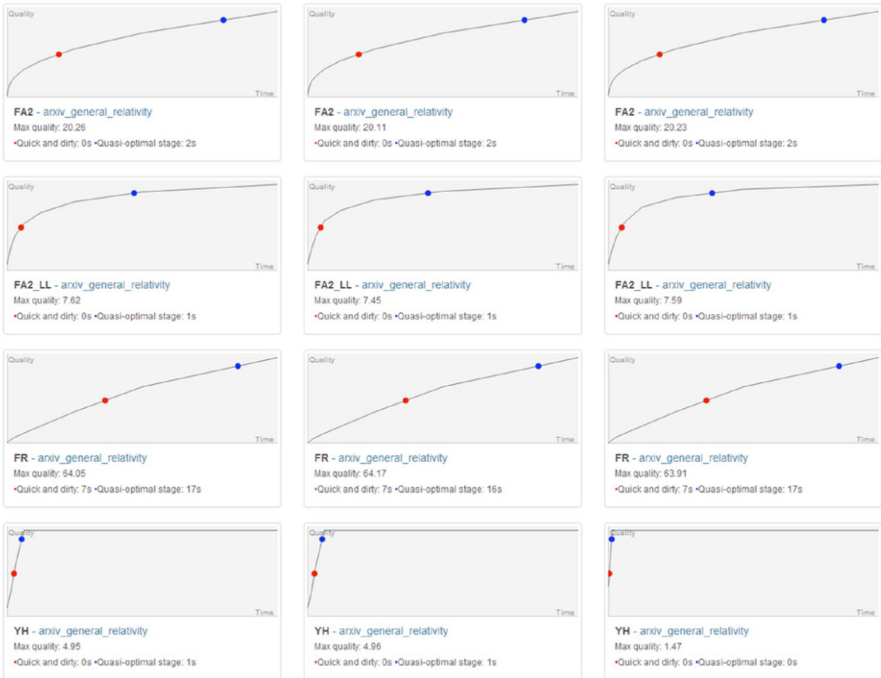


Figure 10. Records for a single network. Evolution of the layout quality for a single network over 2048 steps. Rows are the 4 different layouts and columns the 3 different randomizations. The red dot is the "Quick and dirty point" where 50% of the maximum quality is reached, and the blue dot is the "Quasi-optimal point" where 90% of the maximum quality is reached. The full visualization is available at this URL: https://github.com/medialab/benchmarkForceAtlas2/tree/master/benchmarkResults.
doi:10.1371/journal.pone.0098679.g010

define the swinging $swg(n)$ of a node n as the divergence between the force applied to n at a given step and the force applied n at the previous step. Intuitively, the more the node is asked to change direction, the more it swings. $F_{(t)}(n)$ it the result force applied to n at step t.

$$swg_{(t)}(n) = |F_{(t)}(n) - F_{(t-1)}(n)| \tag{8}$$

For a node moving towards its balancing position, $swg(n)$ remains close to zero. A node that is diverging, on the other hand, has a high swinging and its movement needs to be slowed down to make it converge. The speed $s(n)$ of a node n determines how much displacement $D(n)$ will be caused by the resultant force $F(n)$: $D(n) = s(n)F(n)$. The resultant force is the sum of all forces applied to each node (attraction, repulsion and gravity: $F = F_a + F_r + F_g$). So in ForceAtlas2 the speed is different for every node, and computed as follows:

$$s(n) = \frac{k_s s(G)}{(1 + s(G)\sqrt{swg(n)})} \tag{9}$$

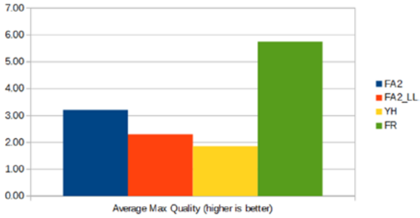
$s(G)$ is the global speed of the graph (see below). k_s is a constant set to 0.1 in Gephi's implementation.

The more a node swings, the more it is slowed. If there is no swinging, the node moves at the global speed. As a protection, we implemented an additional constraint that prevents the local speed from being too high, even in case of very high global speeds.

$$s(n) < \frac{k_{smax}}{|F(n)|} \tag{10}$$

$k_{smax} = 10$ in Gephi's implementation.

	FA2	FA2_LL	YH	FR
Average Max Quality (higher is better)	3.21	2.30	1.85	5.75
Average Quasi-Optimal Time (ms) (lower is better)	638	1,184	333	20,201
Average Quick and Dirty Time (ms) (lower is better)	68	134	98	7,853



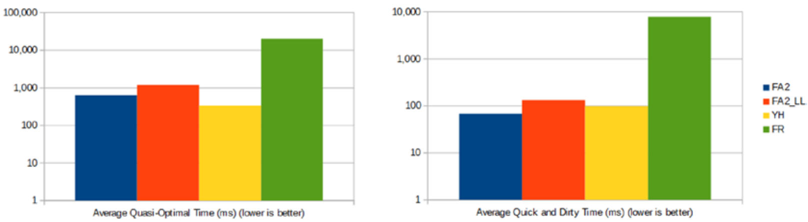


Figure 11. Overall results of the benchmark. Note that the second and third charts have logarithmic scales. FR is really slow, YH has a good performance and FA2 has a good quality.
doi:10.1371/journal.pone.0098679.g011

Adapting the Global Speed

At each step, two global values are computed and used to set the global speed: the global swinging and the global effective traction.

The global swinging $swg(G)$ represents the quantity of erratic movement present in the global movement of the graph. It is the sum of local swinging values, weighted by the degree of each node as in our repulsion force (degree+1).

$$swg(G) = \sum_{n} (deg(n)+1) swg(n) \qquad (11)$$

The effective traction $tra(n)$ of a node is the amount of "useful" force applied to that node. Effective traction is the opposite of swinging: forces that contribute to the convergence. It is defined as an average:

$$tra_{(t)}(n) = \frac{|F_{(t)}(n) + F_{(t-1)}(n)|}{2} \qquad (12)$$

If a node keeps its course, then $tra(n) = F(n)$. If it goes back to its previous position (a perfect swinging) then $tra(n) = 0$.

The global effective traction $tra(G)$ is the weighted sum of effective tractions of nodes:

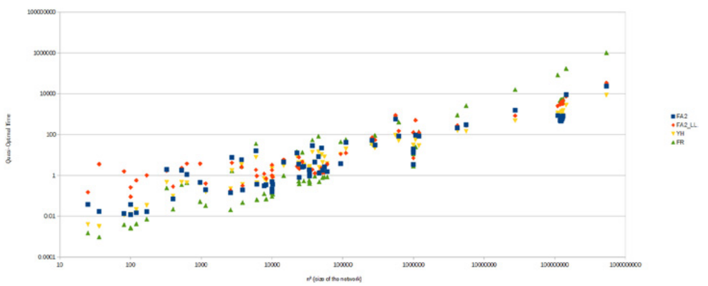


Figure 12. Quasi-Optimal Time over network size. The lower is the better. Note that both scales are logarithmic. On small networks, FR is the best while FA2_LL is slower. On large networks, FR has a poor performance while other algorithms perform similarly on large networks.
doi:10.1371/journal.pone.0098679.g012

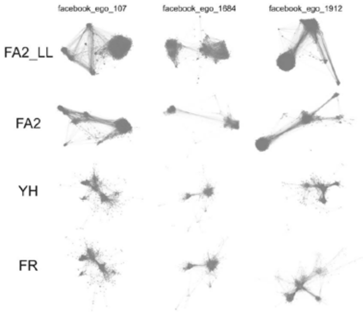


Figure 13. Layouts give visibly different results. We find that FA2_LL and FA2 are more readable, because the different areas of the network are more precisely defined. However, we do not know any quality measure that captures this phenomenon.
doi:10.1371/journal.pone.0098679.g013

$$tra(G) = \sum_{n} (deg(n)+1) tra(n) \tag{13}$$

The global speed $s(G)$ keeps the global swinging $swg(G)$ under a certain ratio τ of the global effective traction $tra(G)$ and is defined as follows:

$$s(G) = \tau \frac{tra(G)}{swg(G)} \tag{14}$$

The ratio τ represents the tolerance to swinging and is set by the user.

NB: During our tests we observed that an excessive rise of the global speed could have a negative impact. That is why we limited the increase of global speed $s_{(t)}(G)$ to 50% of the previous step $s_{(t-1)}(G)$.

Details on this Strategy

Our initial idea was to get the optimal speed under every circumstance, and avoid a "speed" setting that users do not manage easily. We did not succeed, and we still have it under the name of "Tolerance". Below, we explain the strategy we adopted. An optimal global speed is a similar idea to simulated annealing [6]. However, it is not the same because we have to prevent the freezing of the network. Simulated annealing is to find the right way to "cool down" the network, to reduce its speed so that it convergences more efficiently. Intuitively, the network can go faster at the beginning, since it is about finding its general shape, and needs more precision in the end, for the details. In more scientific terms, simulated annealing is about shortening the steps in the end for refining the spatialization, and stopping it. Yifan Hu [7] uses this technique at the end, during a refining phase. However he remarks that "for an application of a force-directed algorithm from a random initial layout, an adaptive step length update scheme is more successful in escaping from local minimums. […] Step length can increase as well as reduce, depending on the progress made". Yifan Hu remarks that out of the refining phase, an adaptive speed is about "heating" as well as "cooling", because escaping a local minimum may need more speed (heating). This applies to our scenario, since there is no refining phase in a continuous algorithm. Yifan Hu evaluates the convergence of the network and adapts its speed in consequence. Our "global speed" plays the same role, but we evaluate the convergence differently. Yifan Hu relies of the variation of global energy, while we rely on the regularity of applied forces (effective traction). The reason is that we have also a local speed optimization, like GEM [5], and that we need some homogeneity between the global speed and the local speed.

We explained that the local speed aims at providing more precision to nodes that fail at converging. Like GEM, we try to minimize swinging (oscillations). The local speed can slow the nodes down, but cannot speed them up. Even if the node requires more speed, it is limited by the global speed. The global speed determines the global movement, it is an "adaptive heating" rather than an "adaptive cooling". It is as high as possible, in the limit of a certain amount of global swinging determined by the "Tolerance" setting. The local speed regulates the swinging while the global speed regulates the convergence. But the regulation of convergence is indirect, since we just compare the global effective traction with the swinging. We rely here on the assumption that oscillation denotes a lack of convergence. This assumption is reasonable, even if we know that it is false under certain circumstances (the swinging of a node propagates to its neighbors). GEM also relies on this assumption.

Comparison with other Algorithms

Here, we compare ForceAtlas2 to the recent algorithm of Yifan Hu and to the old and classic layout of Fruchterman and Reingold. We did not compare it to OpenOrd, which is very efficient, but is not a continuous layout. Nor did we compare it to GEM because it is not implemented in Gephi (that we used as a benchmarking tool). We also compared the LinLog variant of ForceAtlas2 because we had no other implementation (they are very close).

We want to evaluate the speed as well as the quality of each algorithm on different networks. Different measures exist to evaluate the quality of a spatial arrangement of the nodes. H. Purchase uses aesthetic criteria [21] while A. Noack prefers interpretive properties [18]. We chose Noack's "normalized[endv] atedge length" (15) because it is more adapted to scale-free networks and has been used by Noack to evaluate Fruchterman-Reingold and LinLog.

$$Q_{Noack}(p) = \frac{\sum_{\{n_1;n_2\}\in E} distance(p(n_1),p(n_2))}{|E|} \Big/ \frac{\sum_{\{n_1;n_2\}\in N^2} distance(p(n_1),p(n_2))}{|N^2|} \tag{15}$$

We will observe that contrary to our expectations, Fruchterman-Reingold performs better than LinLog, while LinLog is empirically more readable than Fruchterman-Reingold (we provide more details below). However this m easure is very good at capturing the process of a layout algorithm applied to a given network. Unlike other measures like edge crossings [21], it is sensitive to the smallest displacements. We rely on it to track the behavior of each benchmarked algorithm and to identify when the convergence is reached. Even if the measure is not fully satisfying to evaluate the quality, it is a good way to evaluate the speed.

Noack's measure has another drawback. It is better when it is lower, which may lead to interpretation issues. We decided to invert the measure to be clearer (16):

$$Q(p) = \frac{1}{Q_{Noack}(p)} \qquad (16)$$

At each step of the tested algorithm, we compute the quality for current positions. All the layouts, by definition, improve the quality of the spatialization. We compare the best quality they reach, and how many steps are needed to reach a good convergence (performance). Figure 8 pictures the impact of the adaptive local speed feature using this protocol. The featured network is "facebook_ego_0" from our dataset. We compare the actual implementation to variants where we fixed the local speed at different values (the algorithm is otherwise similar to the implementation described above). We observe different scenarios. If the speed is too low (0.001), the convergence is slow and we do not have enough steps to see the final quality. If the speed is too high (0.1) the quality stagnates early on, because of oscillations. A medium value of 0.01 has a good convergence and a good final quality, but the adaptive local speed achieves even better on convergence as well as on final quality. We reproduced this protocol on the other facebook ego-networks of the dataset and the results confirm this behavior, as pictured in Figure 9.

We benchmarked our algorithm with a dataset of 68 networks from 5 to 23,133 nodes. We tried to gather varied networks corresponding to the actual use of Gephi (a lot of social networks, and scale-free networks in general). Most of these networks are from the Stanford Large Network Dataset Collection (http://snap.stanford.edu/data/) and include social networks (Facebook and Twitter ego-networks), collaboration networks (from Arxiv) and autonomous systems (peering information inferred from Oregon route-views). Some networks come from the Gephi datasets, and include biological networks (neural network of C. Elegans, protein-protein interaction network in yeast). The others are generated with Gephi and include trees, random networks and small-world networks. Our dataset and the description of each network are included in the online repository of the benchmark (https://github.com/medialab/benchmarkForceAtlas2).

We compared four different algorithms: ForceAtlas2 (FA2), its LinLog variant (FA2_LL), Fruchterman-Reingold (FR) and Yifan Hu (YH). We used the default settings, with the exception of a few settings. FA2 and FA2_LL have different settings for small, medium and large networks: we used the medium settings on every network. FR was so slow that we updated its speed to 10 and its "Area" setting to 1000 so that the resulting layout has a comparable size. We also set the FA2_LL "Scaling" to 0.1 for the same reason.

Exact settings are:

- FA2: BarnesHutTheta 1.2; EdgeWeightInfluence 1.0; Gravity 0.0; JitterTolerance 1.0; ScalingRatio 2.0; AdjustSizes false; BarnesHutOptimize true; LinLogMode false; OutboundAttractionDistribution false; StrongGravityMode false
- FA2_LL: BarnesHutTheta 1.2; EdgeWeightInfluence 1.0; Gravity 0.0; JitterTolerance 1.0; ScalingRatio 2.0; AdjustSizes false; BarnesHutOptimize true; LinLogMode true; OutboundAttractionDistribution false; StrongGravityMode false
- YH: BarnesHutTheta 1.2; ConvergenceThreshold 1.0E-4; InitialStep 20.797; OptimalDistance 103.985; QuadTreeMaxLevel 10; RelativeStrength 0.2; StepRatio 0.95; AdaptiveCooling true
- FR: Area 1000.0; Gravity 0.0; Speed 10.0

Even if some of the networks are large (23,133 nodes and 186,936 edges) while others are very small (5 nodes and 5 edges), we wanted to use the same benchmark protocol. On the one hand, computing the layout quality is time-consuming on the biggest networks, and the convergence is slow (more than 1,000 steps). We did not have the time to compute the layout quality for hundreds of steps on each network. On the other hand, the small networks converge in a few steps, and we wanted to be able to spot the moment it happens. We had to track the early steps. As a compromise, we decided to compute layout quality each "power of 2" step: 1, 2, 4, 8… up to 2048. The quality evolves a lot at the early stages of the spatialization, and then reaches a more static state. Our protocol provides the early behavior of each algorithm as well as its long-term results. We also observed that some layouts cause oscillations (as pictured in Figure 8), so we computed each "power of 2 plus one" step: 2, 3, 5, 9… up to 2049. We averaged the quality at each "power of 2" step with the next step to remove oscillations.

Each network was randomized three times. The three random assignments are saved in the dataset. You can download the dataset here: (https://github.com/medialab/benchmarkForceAtlas2/blob/master/dataset.zip). The benchmark resulted in 816 records of the layout quality at different steps. You can visualize these records there http://medialab.github.io/benchmarkForceAtlas2/and download them https://github.com/medialab/benchmarkForceAtlas2/tree/master/benchmarkResults. Each file was analyzed to find the maximum quality, and two key moments. The "Quick and dirty" point is reached at 50% of the maximum quality, while the "Quasi-optimal" point is reached at 90% of the maximum quality. The first corresponds to an estimation of a rough spatialization while the second approximates a satisfying layout. A sample of these records is pictured in Figure 10, and the full visualization is available online. We expressed these points in milliseconds using the timestamps in the records. The maximum quality, the "Quick and dirty" time (QND Time) and the "Quasi-optimal" time (QO Time) are averaged over the 3 randomizations for each layout.

The overall results, as pictured in Figure 11, show that FR reaches the best quality but is too slow. Its performance is so poor on large networks that it cannot be used without an optimized implementation. YH, FA2 and FA2_LL have a comparable quality and performance, and Yifan Hu is quicker while ForceAtlas2 has a better quality. The details give us some useful informations about the specificities of each algorithm. Yifan Hu has the best performance, with an average QO Time of 333 ms, followed by ForceAtlas2 (638 ms), the LinLog variant (1,184 ms) and finally Fruchterman-Reingold (20,201 ms). FR is not optimized and was really slow on the largest networks. The Figure 12 shows the differences of algorithms depending on the size of the network. FR is most suitable for smaller networks and the worst for the largest. FA2 and YH are similar at all scales while FA2_LL is significantly worse on small networks, but not so much on the largest. FA2 is the quickest to reach its Quick and Dirty point in average (68 ms). YH (98 ms) and FA2_LL (134 ms) are not much different, but they highlight the good convergence of FA2 in the early steps. FR is also far behind (7,853 ms).

We find empirically that it is easier to identify the clusters in FA2 and FA_LL than in FR and YH. Noack's measure does not reflect this observation, and we do not know how to measure this phenomenon. However we think it is useful to show a sample result of each layout. The Figure 13 compares the result of the four layouts in three different cases (Facebook ego-networks). We find that the different areas of the network are more precisely defined with FA2_LL and FA2. Even if this is debatable, it is clear that the layouts have different visual properties that are not captured by the quality measure we used. A more advanced benchmark would require a different way to capture the visual properties of the layouts.

In conclusion ForceAtlas2 compares to Yifan Hu in terms of quality and performance. Yifan Hu has a better performance on small networks while ForceAtlas2 has a better measured quality, though evaluating the readability of different layouts would require a different discussion and protocol. The LinLog mode of ForceAtlas2 brings more quality at the price of performance, and Fruchterman-Reingold performs poorly on large networks.

Discussion: Designing a Generic, Continuous Layout

The visualization of a network involves design choices. We think users have to be aware of the consequences of these choices. The strategy we adopt in Gephi is to allow users to see in real time the consequences of their choices, learning by trial and error. Interaction, we believe, is the key to understanding. While developing the Gephi user experience, we strongly desired a "live" spatialization process. Hiding it may lead users to believe that the placement is unique or optimal. Non-expert users need to observe the spatialization process and even to interact with it. Manipulating a graph while it spatializes helps to understand the difference between a graph layout and a Cartesian projection. The effect of the settings can be observed and understood. It helps to figure out that spatialization is a construction that involves the responsibility of the user.

Users can act on the network by changing the ranking of the nodes, or filtering nodes and edges, even creating new entities. ForceAtlas2 passes on modifications in real time, re-computing forces and continuously updating the placement of nodes. It is possible to "play" with the network. Since it is intuitive for users, developers can integrate other features on top. For instance we integrate the visualization of a dynamic network just as a particular case of dynamic filtering: the real-time layout updates the structure according to the specified time span. For an example see the dynamic visualization of a Twitter conversation, http://gephi.org/2011/the-egyptian-revolution-on-twitter.

Data monitoring is a basic use case of network visualization. With Gephi we intend to foster advanced uses: data exploration and map making. These uses are more demanding. Exploring the data may require searching for an adapted layout: a satisfactory algorithm with satisfactory settings. We cannot discuss here how and why some algorithms are better choices for certain networks, but we can give basic example cases. ForceAtlas2 is not adapted to networks bigger than 100,000 nodes, unless allowed to work over several hours. On the contrary, OpenOrd [8] is not adapted to networks of fewer than 100 nodes, because its side effects are too visible at this scale. Certain algorithms are more adapted to certain sizes, as well as certain densities, or certain community structure. Certain energy models provide a better depiction of certain network types. Alternative energy models are relevant features to diversify the algorithm's applications. The *LinLog*, *edge weight* and *gravity* settings are such options, fostering a better exploration of the structure. Map making requires different features. Its purpose is to make the network fit in a limited graphic space. *Scaling* and *gravity* settings help users to produce a more compact network. The *overlapping prevention* provides more readability to the result. Finally, some features are implemented just for performance, such as the Barnes Hut's optimization (*approximate repulsion*) and adaptive speeds. Even in this case we try to provide explicit settings to the user (*Tolerance (speed)*).

Integrating various features forces us to adapt some of them. We bring homogeneity in the different forces we implement. First we weight the nodes by degree plus one instead of just the degree (we cannot ignore nodes of degree 0). Secondly we adapt the *gravity* energy model to the repulsion force to limit its side effects. When repulsion is weighted in a certain way (for instance with the *dissuade hubs* setting) then the gravity is weighted the same way. We also normalized certain features to provide a smoother user experience. When *dissuade hubs* is activated, we compute a normalization to ensure that the total energy with the alternative forces is the same to the reference forces. Thanks to this trick, the network keeps a comparable spreading in the graphic space. Not that the *LinLog* energy model does not benefit from such a normalization, so you have to adjust the scaling when you activate it.

Conclusion

As more and more people deal with relational data, network visualization assumes a key importance. ForceAtlas2 is our practical contribution to network sciences. It is not based on a new conception of force-directed layouts but it implements many features from other well-known layouts [7] [11] [5]. However, by its design and features, it aims to provide a generic and intuitive way to spatialize networks. Its implementation of adaptive local and global speeds gives good performances for network of fewer than 100000 nodes, while keeping it a *continuous* layout (no phases, no auto-stop), fitting to Gephi user experience. Its code is published in Java as a part of Gephi source code (https://github.com/gephi/gephi/tree/master/LayoutPlugin/src/org/gephi/layout/plugin/forceAtlas2).

Author Contributions

Conceived and designed the experiments: MJ TV. Performed the experiments: MJ TV. Analyzed the data: MJ SH. Contributed reagents/materials/analysis tools: MJ SH MB. Wrote the paper: MJ TV SH MB. Implemented the algorithm: MJ MB.

References

1. Bastian M, Heymann S, Jacomy M (2009) Gephi: an open source software for exploring and manipulating networks. In: International AAAI Conference on Weblogs and Social Media. Association for the Advancement of Artificial Intelligence.
2. Diminescu D (2008) The connected migrant: an epistemological manifesto. Social Science Information 47: 565–579.
3. Batagelj V, Mrvar A (1998) Pajek-program for large network analysis. Connections 21: 47–57.
4. Adar E (2006) Guess: a language and interface for graph exploration. In: Proceedings of the SIGCHI conference on Human Factors in computing systems. ACM, 791–800.
5. Frick A, Ludwig A, Mehldau H (1994) A fast adaptive layout algorithm for undirected graphs (extended abstract and system demonstration).
6. Davidson R, Harel D (1996) Drawing graphs nicely using simulated annealing. ACM Transactions on Graphics (TOG) 15: 301–331.
7. Hu YF (2005) Efficient and high quality force-directed graph drawing. The Mathematica Journal 10: 37–71.
8. Martin S, Brown WM, Klavans R, Boyack KW (2011) OpenOrd: an open-source toolbox for large graph layout. In: Society of Photo-Optical Instrumentation Engineers (SPIE) Conference Series. volume 7868 of Society of Photo-Optical Instrumentation Engineers (SPIE) Conference Series.
9. Walshaw C (2001) A multilevel algorithm for force-directed graph drawing. In: Graph Drawing. Springer, 171–182.
10. Kamada T, Kawai S (1989) An algorithm for drawing general undirected graphs. Information processing letters 31: 7–15.

11. Noack A (2007) Energy models for graph clustering. J Graph Algorithms Appl 11: 453–480.
12. Noack A (2009) Modularity clustering is force-directed layout. Physical Review E 79.
13. Newman MEJ (2004). Analysis of weighted networks. Arxiv:cond-mat/0407503.
14. Newman MEJ (2006) Modularity and community structure in networks. Proceedings of the National Academy of Sciences 103: 8577–8582.
15. Krzywinski M, Birol I, Jones SJ, Marra MA (2012) Hive plotsrational approach to visualizing networks. Briefings in Bioinformatics 13: 627–644.
16. Eades P (1984) A heuristic for graph drawing. Congressus Numerantium 42: 149–160.
17. Fruchterman TMJ, Reingold EM (1991) Graph drawing by force-directed placement. Softw: Pract Exper 21: 1129–1164.
18. Noack A (2007) Unified quality measures for clusterings, layouts, and orderings of graphs, and their application as software design criteria. PhD thesis, Brandenburg University of Technology, Cottbus, Germany.
19. Kleinberg JM (1999) Authoritative sources in a hyperlinked environment. J ACM 46: 604–632.
20. Barnes J, Hut P (1986) A hierarchical o(n log n) force-calculation algorithm. Nature 324: 446–449.
21. Purchase H (2002) Metrics for graph drawing aesthetics. Journal of Visual Languages and Computing 13: 501–516.

APPENDIX C. VISUAL NETWORK EXPLORATION FOR DATA JOURNALISTS

Book chapter.

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VISUAL NETWORK EXPLORATION FOR DATA JOURNALISTS

Tommaso Venturini, Mathieu Jacomy, Liliana Bounegru, and Jonathan Gray

Networks are classic but under-acknowledged figures of journalistic storytelling. Who is connected to whom and by which means? Which organizations receive support from which others? What resources or information circulate through which channels, and which intermediaries enable and regulate their flows? These are all customary stories and lines of inquiry in journalism, and they all have to do with networks. Additionally, the recent spread of digital media has increasingly confronted journalists with information coming not only in the traditional form of statistic tables but also of relational databases. Yet journalists have so far made little use of the analytical resources offered by networks.

To address this problem in this chapter, we examine how 'visual network exploration' may be brought to bear in the context of data journalism to explore, narrate, and make sense of large and complex relational datasets. We illustrate this technique through a network of French information sources compiled by *Le Monde*'s The Décodex. We establish that visual exploration is an iterative process where the demarcation of categories and territories are entangled and mutually constitutive. To enrich investigation, we suggest ways in which the insights of the visual exploration of networks can be supplemented with simple statistics on the distributions of nodes and links. We conclude with reflection on the knowledge-making capacities of this technique and how these compare to the insights that journalists have used in the Décodex project – suggesting that visual network exploration is a fertile area for further exploration and collaborations between data journalists and digital researchers.

Introduction

Few people know as well as journalists that the world is made of relations. Following alliances, unveiling links, and unraveling threads are, and have long been, a central part of their investigations. If social scientists can speculate about long-standing structures and global arrangements, journalists have no such leisure. Their work consists in tracing the specific associations that connect individuals and institutions to uncover how lumps of money, influence, and knowledge are exchanged through them and where unethical behavior, corruption, fraud, or unfair political influence may occur. The advent of digital technologies has made such work both easier and more difficult: easier, because it has increased the traceability of economic and political associations; more difficult, because it has submerged journalists under more information than their investigative toolkit is used to handling.

When, for example, the reporters of the International Consortium for Investigative Journalism (ICIJ) received the 2.6 terabytes and 11.5 million documents composing the so-called 'Panama Papers', they obviously could not process them manually (Baruch and Vaudano, 2016). Note that this is not just a 'big data' problem. The trouble with the leak was not only its size but the fact that its interest came from the links it established between specific individuals and particular tax havens. Extracting 'key' figures through statistical aggregation or abstracted computational models would miss the point of many of the stories that journalists were most keen to explore. The inquiry could not simplify the dataset but had to explore each and every one of the connections it exposed. This was done, among other ways, through a tool called *Linkurious* (http://linkurio.us), whose interest comes less from its computational power than from the way in which it allows its users to see and follow the connections of a network.

The Panama Paper case is interesting but also interestingly isolated. Despite long-standing interest, the use of networks in journalism remains comparatively marginal (cf. Bounegru et al., 2016 for an overview of the emerging uses of networks in journalism). The reasons are not difficult to imagine. Graph mathematics is more demanding and less widely known than traditional statistical approaches and does not come with the same readily accessible and publicly recognized vocabulary of visual motifs. With all its computational power, graph mathematics does not fit journalistic needs because it tends to be obscure for both reporters and their readers.

In this chapter, we address this difficulty by suggesting a technique for the visual exploration of networks. As we will try to show, when performed correctly, the visual representation of networks translates some of the most important graph structures into graphical variables (thereby supporting investigative work) and allowing the interpretation of networks with conventions similar to those developed for geographical maps (thereby remaining legible for a large audience). After having introduced the mathematical and historical bases of our approach, we will present our technique for the visual exploration of networks. Using as an example the network of the French information sphere, we will illustrate the recursive work of interpretation and categorization that allows reading the network as an organized territory. Visual network exploration, which is growing in prominence amongst digital methods researchers for social and cultural research, may be useful not only for studying media landscapes but also for digital journalism practitioners who are interested in exploring and telling stories with networks and relational data.

Understanding force-directed layouts

Far from being merely aesthetic, the graphical representation of networks has an intrinsic hermeneutic value, which you will have experienced if you have ever used a public transportation map. Such maps are distinctively different from road maps or city maps. It is not only that transportation maps are simpler (the level of details depending only on the resolution of the map), it is that they represent a network and not a geographical territory. An illustration of this difference can be found in the famous map of the London tube as designed by Harry Beck in 1933. Before Beck's redesign, the diagram was a classic geographical map locating stations according to their coordinates. After the redesign, it became the network of correspondences we are still using today. The gain in legibility is evident, as the function of transportation maps is not to situate stations in urban space but relative to each other, so as to help users to move from one to another (a type of orientation that resembles strikingly to one used by traditional sea navigators; see, for example, Turnbull, 2000: 133–165).

Another example of such a mapping approach comes from early work in social network analysis (Freeman, 2000). Jacob Moreno, founder of SNA, is explicit about the importance of visualization: "A process of charting has been devised by the sociometrists, the sociogram, which is more than merely a method of presentation. It is first of all a method of exploration" (1953: 95–96). In an interview released by Moreno to the *New York Times* in 1933, network analysis is presented as a 'new geography'. More important than the title, however, is the figure that accompanies that interview, depicting friendships among fourth-grade pupils (see Figure 20.1). The sociogram presented by these figures powerfully reveals how friendship is not equally distributed in the class. One only need to know that triangles represent boys and circles girls to see how inter-gender relationships are discouraged at that specific age (or at least the declaration of such friendships). The trick, of course, only works because the nodes are not positioned randomly in the space but in a way that minimizes line crossing (in Moreno's own words "the fewer the number of lines crossing, the better the sociogram" (1953: 141)). It is because triangles are pushed on one side and circles on another that it is easy to spot the existence of a single inter-gender connection.

Moreno's rule of spatialization is easy to follow on a graph of a few dozen nodes and edges but impracticable on larger networks. Graphs with thousands of nodes and edges are so intricate

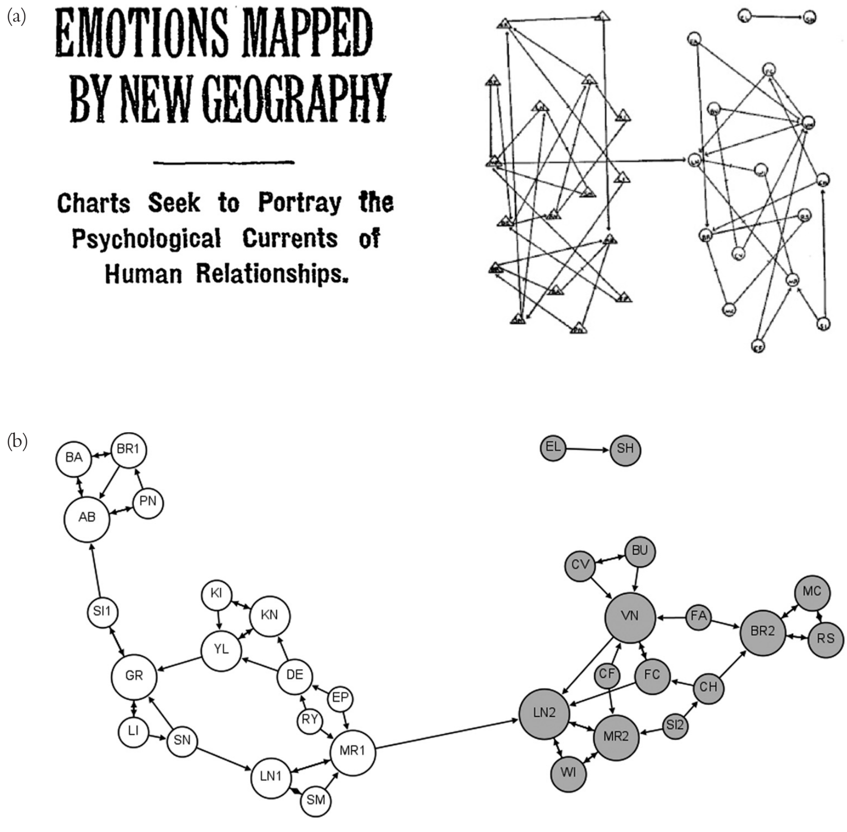


Figure 20.1 Sociogram representing friendship among school pupils (original title and image accompanying Moreno's 1933 *New York* Times interview) (a) in the original version and (b) in the modern force-directed spatialization

that the direct counting of line-crossings becomes prohibitively time consuming. An indirect approach consists of drawing closer the connected nodes to minimize the length of the edges and therefore the possibility of crossings. But even in this case, since each node may be connected to several other nodes that are themselves connected to many other nodes, minimizing the length of the edges is far from a trivial exercise.

Thus, we might explore the network using a technique called 'force-directed spatialization'. Such spatialization follows a physical analogy: nodes are charged with a repulsive force that drives them apart, while edges act as springs binding the nodes that they connect. Once the algorithm is launched it changes the disposition of nodes until it reaches a balance of such forces (Jacomy et al., 2014). Such equilibrium reduces line-crossings and improves the legibility of the graph. Früchterman and Reingold (1991), who proposed the first efficient force-directed algorithm, cite line crossing as the second of their aesthetic criteria.

Yet scholars working with networks soon realized that avoiding line crossing is not the most interesting effect of force-directed layouts. At equilibrium, the visual density of nodes and edges becomes an approximate but reliable proxy of the mathematical structure of the graph (for a detailed mathematical proof, see Venturini et al., forthcoming). Groups of nodes gathering in the layout tend to correspond to the clusters identified by community-detection techniques (Noack, 2009); structural holes (Burt, 1995) tend to look like sparser zones; central nodes move toward middle positions; and bridges are positioned some way between different regions (Jensen et al., 2015).

The trick of force-directed algorithms is all the more remarkable, given that the space of networks is relative rather than absolute (it can be rotated or mirrored without distortion of information) and that it is a consequence and not a condition of element positioning. In traditional geographical representation, the space is defined *a priori* by the way the horizontal and vertical axes are constructed. Points are projected on such preexisting space according to a set of rules that assign a univocal position to a pair of coordinates. The same is true for any Cartesian diagram (scatterplots, for instance) but not for networks, in which the space is defined by the position of the nodes and not the other way around.

Despite such differences (which should not be forgotten), force-directed algorithms allow reading networks as geographical maps, translating complicated mathematical concepts into more conventional vocabulary of regions and margins, path and landmarks, centers and peripheries (Lynch, 1960). This is a crucial advantage that explains why force-directed algorithms have become the *de facto standard* of network visualization: they facilitate the exploration of networks and relations by means of more familiar and intuitive spatial metaphors, as well as through less familiar computational and statistical metrics.

The Décodex: a controversial case study

In the following pages, we will illustrate the technique of visual network exploration drawing on a concrete example. Our case study is a network of websites extracted from a listing compiled by the French journal *Le Monde*. Since 2009, a group of journalists gathered under the name of *Les Décodeurs* (www.lemonde.fr/les-decodeurs/article/2014/02/12/l-equipe-des-decodeurs_4365082_4355770.html) has verified the accuracy of thousands of stories circulating in the French blogosphere and in social media. In January 2017 (at the beginning the French presidential campaign), *Les Décodeurs* launched an online tool called the Décodex (www.lemonde.fr/verification), allowing readers to search for the most important sources of online information relevant to French public debates (though not necessarily in French). Each source is accompanied by a short description and, more crucially, by an evaluation of its trustworthiness according to the journalists of *Le Monde*.

Not surprisingly, the classification provided by *Les Décodeurs* has stirred considerable debate in French media spheres. Several of the sources categorized as imprecise or unreliable, along with other newspapers and blogs, have contested the Décodex, with critique spanning from challenging the way in which websites are oversimplistically classified to questioning the right of *Le Monde* (which is itself a rival source of information) to note the reliability of other websites, to disputing the legitimacy and interest of such classification in general (arguing that some of the websites in the list mean to circulate opinions rather than information). *Les Décodeurs* themselves admitted the difficulty of their exercise, the many ambiguities that they were obliged to decide on, and the errors and inaccuracies that may have derived from them. At the same time, they defended their work by pointing to the increasing quantity of false or partisan information circulating online and by affirming their openness to discussing their classification and revising it if necessary.

The controversy around the Décodex is a good example of difficulties connected to the detection of fake news online (Bounegru et al., 2017), but also of the more general debates surrounding all kind of classifications. Categorizing things is never a self-evident or innocent practice (Bowker and Star, 1999) and should always be carried out with the greatest caution. This is true for the initial classification of the Décodex, but it is also true for the network extracted from it. As we will see in the following pages, the visual exploration of network involves a constant toing and froing of categorization and observation, typology, and topology.

To build our example network, we have extracted, in collaboration with *Les Décodeurs*, all the websites contained in the Décodex and investigated the way in which they cite each other. To do so, we employed Hyphe (http://hyphe.medialab.sciences-po.fr), a web crawler developed by the médialab of Sciences Po that facilitates the exploration of websites and following the hyperlinks present in their pages (Girard, 2011; Girard et al., 2012; Jacomy et al., 2016). All the websites comprising the Décodex corpus have been crawled at a depth of one click, starting from the homepage. We so obtained a network with 653 nodes and 5,943 edges. While *Les Décodeurs* focus on editorial judgments about how to *classify* websites in the French media landscape, our network exploration examines the relations between them and other websites by means of their *linking practices*. While some researchers focus on how networks are held together through financial ties, organizational affiliations, business relationships, and family and social relations, we consider their relations according to the hyperlink, in accordance with a longer tradition of digital methods, digital sociology, and new media studies research (see, e.g., Marres and Rogers, 2005; Rogers, 2013)

The treatment of social platforms (such as Facebook, Twitter, YouTube, etc.) in our crawl requires some additional explanation. These platforms are both sources of information as a whole and containers of multiple individual sources in the form of pages or accounts. Since extracting all the hyperlinks from a site as large as Facebook would have been impossible, we only crawled the accounts that were specifically mentioned in the Décodex. We have, however, kept a record of all the links pointing toward the main social media platform to investigate how they are cited by the other websites of our corpus.

A visual exploration of the Décodex network

The visual exploration of networks exploits three visual variables to graphically represent their features: position, size, and hue (for a definition of these variables and their semiotic affordances, see Bertin, 1967). For the reasons discussed earlier, position is crucial in translating the mathematical characteristics of the graphs. Force-directed layouts create regions where numerous nodes are densely assembled and regions that are less crowded. These differences of density, determined by the uneven distribution of links, reveal the uneven association among the entities of the network. Everything may be connected in this world, but not everything is *equally* connected.

Discerning the spatial structure of networks, however, is not always straightforward. In the easiest cases, the difference in the density of association is such that clusters appear as well-defined knots of nodes and edges separated by empty (or almost empty) zones. These zones are called "structural holes" (Burt, 1995), and, when they exist, they provide a crucial guidance for the interpretation of the network. Thanks to the ruptures created by structural holes, the boundaries of clusters can be easily detected, like cliffs separating a plateau from a valley. Most natural and social networks, however, do not exhibit such a clear separation, and the borders of their cluster tend to be gradual as the hillside slopes. The fuzziness of clusters' frontiers is not necessarily an obstacle to their recognition (one can point at a hill even when it is impossible to say exactly where it starts and ends), but it certainly makes their identification more difficult. This is why visual network analysis is often more like an exploratory expedition – where meanings and findings are progressively and hermeneutically generated – than statistical confirmation of a set of preexisting hypotheses (on the difference between exploratory and confirmatory analysis see Tukey, 1977, and Behrens and Chong-Ho, 2003).

This is certainly the case for our Décodex network, which, at a first look, does not present any manifest structural hole or any clear spatial structure. To visualize our network we used two main tools: Gephi (https://gephi.org) for filtering and spatializing the network (using in particular the force-driven algorithm ForceAtlas2) and Graph Recipes (http://tools.medialab.sciences-po.fr/graph-recipes) to tweak the visual rendering of the network (see Figure 20.2). Though no structural holes are evident in the Décodex network, looking closely at the layout makes it possible to notice that the network does not spatialize as a perfect circle but rather in an avocado-like shape with a smaller top and a larger bottom. These irregularities (as weak and subtle as they can be) often suggest the presence of polarizing effects that can be interesting to investigate further.

The first and most crucial way to explore our network is to look at the identity of the nodes that occupy its different regions. This may seem trivial, but it is not. It is a distinct advantage of visual exploration, compared to other forms of statistical analysis, that it does not aggregate the individual entities that compose its corpus: each and every node is visible in the layout and can be interrogated by the researcher. Even on a small network like the one in our example, however, the quantity of nodes can make it difficult (and time consuming) to look at all of them.

This is where the second variable of our visual exploration, *size*, comes in handy. Since, in networks, nodes are defined first and foremost by their connections, we have ranked the nodes according to the number of edges pointing to them. In the jargon of network analysis, this number is called 'in-degree', and nodes with an elevated in-degree are called 'authorities', because they are recognized and referred to by many others. In the previous figure and in all following, we have sized the nodes according to their in-degree so that a greater authority literally translates into increased visual prominence.

Reading the names of websites that occupy the two poles of our avocado, it seems natural to suppose that their separation derives from a linguistic fracture. The websites in the lower part are predominantly French, while those in the upper part are more international. A way to highlight this is to show the uneven distribution of TLD (top-level domain) in the network (Figure 20.3).

The linguistic separation we just highlighted, however, is not particularly surprising or interesting. This kind of division is regularly observed in networks of websites and hyperlinks. Detecting it is important, but in a negative way – it makes us aware that in order to generate more interesting findings, we will have to look *beyond* it.

Further exploring the network, we may notice the role of not just languages but also social network platforms, such as YouTube, Facebook, Twitter, Instagram, and Dailymotion. With the remarkable exception of Wikipedia, all the main social media platforms are located in the middle right of the layout – somewhere in between the English and the French websites (as one would

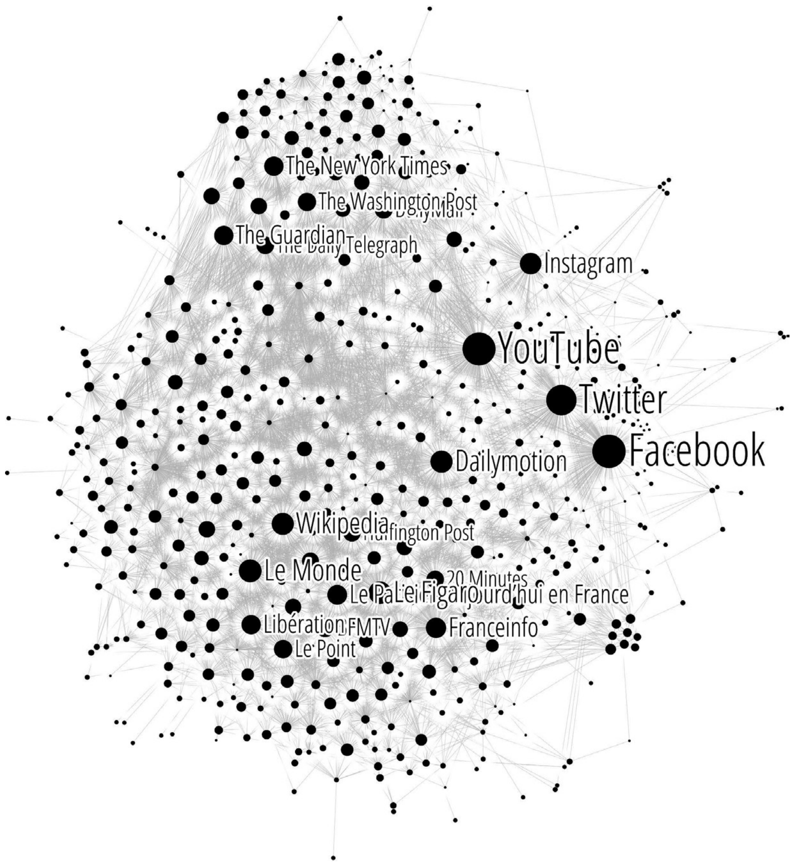


Figure 20.2 The Décodex network spatialized by ForceAtlas2. The size of nodes is proportional to in-degree.

expect given the multilinguality) but also separated from both by their distinctive nature (and possibly by the different way in which they have been treated in the crawl).

Moreover, by focusing on the lower and larger part of the network, we can recognize two different sub-poles, with national sources (such as *Le Monde*, *Le Figaro*, FranceInfo, *Libération*, etc.) occupying most of the lower region and the regional press clustering at the bottom right of the layout (see Figure 20.4).

The distinctive position of the platforms and the national/regional press are both interesting and nontrivial findings, but we can push our analysis further. The way to do so is by playing with the third visual variable exploited by visual exploration of network: the hue of the node. This is a laborious but revealing part of our visual exploration. It consists of categorizing the nodes of the network according to multiple classifications and visualizing these classes on the network as different colors or (as in this chapter) as different shades of gray. It is important to notice that the operation of classifying the nodes and of reading the disposition of classes are not separated but

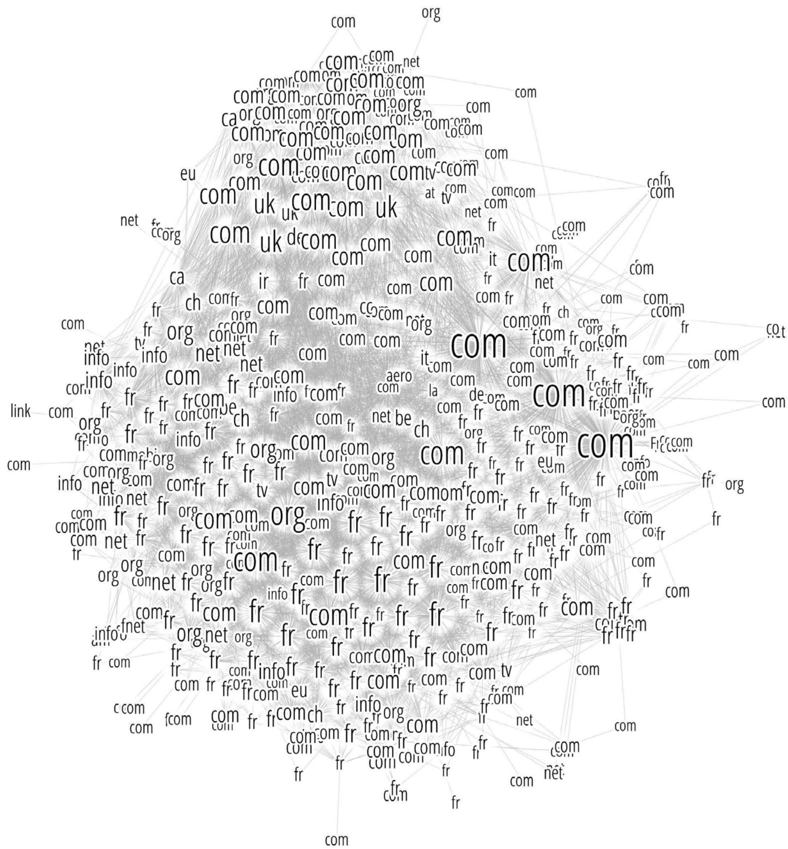


Figure 20.3 Distribution of TDL in the Décodex network

performed at the same time. As will become clear in the following pages, our technique does not consist simply in the projection of a set of preexisting categories on a connectivity-based layout but on recursively using the categories to make sense of the layout and the layout to define the categories. It is important to remember that the color is a 'non-mixable' visual variable. A node can be red or blue, for example, but not the two at the same time. When categorizing nodes, it is therefore necessary to employ exclusive categories. A website, for example, can be classed in the category 'news' or 'satire', but not in both. In the (not uncommon) case of nodes resisting a unique classification, researchers can introduce a residual category such as 'multiple' or 'miscellaneous'.

As a first step in our combined exploration of topology and typology, we will color the nodes of the network according to the original categories of the Décodex. These categories refer to the trustworthiness of the sources, as manually assessed by the journalists of *Le Monde* in the four categories 'reliable', 'imprecise', 'unreliable', and 'satirical'. Precisely because these categories have been defined before and independently from the extraction of the network, their disposition does not follow the spatial articulation of the network. Rather, it is possible to find nodes of every

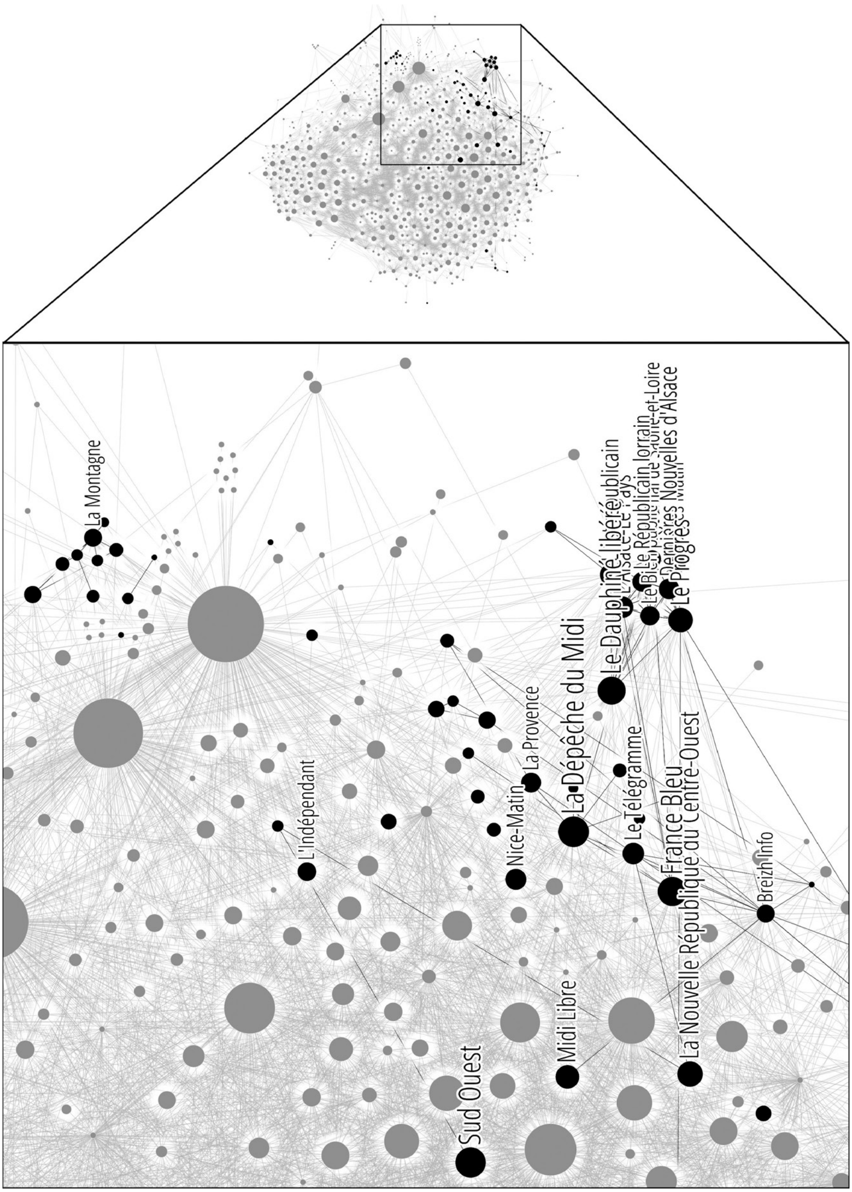


Figure 20.4 Zoom on the French regional press

category in most regions of the network. A remarkable exception is the satirical websites that are to be found on the right side of the layout both in its upper and lower part (see Figure 20.5). Arguably, this position is not due to the hyperlinks between the satirical websites (which do not cite each other very much) but by their strong connection with social media platforms to which all these sites extensively link.

The other classes are distributed more evenly but not randomly. The 'reliable' websites tend to occupy the center of both in the international and French pole, while the 'imprecise' and 'unreliable' take a more marginal position (see Figure 20.6). More interestingly, looking at the lower part of the network, we observe two groups of 'imprecise' and 'unreliable' sources – while a majority of these nodes are positioned above the core of national and reliable websites (and hence in between the French and the international website), a significant minority is located below them.

To account for this separation, we introduce an additional categorization based on the political leaning of the websites (Figure 20.7). In particular, we distinguish the websites that disseminate unreliable or imprecise information because they pursue a right-wing or extreme-right agenda

Figure 20.5 The 'satirical' websites according to the original Décodex classification (nodes have been highlighted by the black color and by doubling their radius despite their low degree)

Figure 20.6 Highlight of the 'reliable' websites (left) and 'unreliable' and 'imprecise' websites (right)

Figure 20.7 Highlight of the 'conspiratorial' websites (left) and 'right' and 'extreme right' websites (right)

(which occupy the center of the network) and the websites exhibiting a more general conspiratorial attitude (which occupy the bottom of the network).

Through our iterative exploration of typology and topology, we have eventually revealed a partitioning of the network that, while invisible at first glance, allows us to interpret some of the main contours of the French media landscape. Though these territories are not separated by clear structural holes, the nodes that they contain are fairly consistent. Interestingly, our final classification produces a homogeneous partition of the layout *not in spite of but because of* its heterogeneity, which mixes linguistic categories, trustworthiness classes, and political leanings. The fact that a nonhomogenous categorization turns up to offer the best characterization of the structure of our network should not come as a surprise. Networks are complex objects that articulate diverse elements through disparate logics. In this, they remind us of a passage by Jorge Luis Borges cited by Foucault (1970) as a perfect example of a heterogeneous classification that, while defying our traditional categories, is nonetheless highly efficient to describe the culture in which it has been elaborated (Figure 20.8). Borges refers to a "certain Chinese encyclopaedia" in which animals are classified as

> (a) belonging to the Emperor, (b) embalmed, (c) tame, (d) suckling pigs, (e) sirens, (f) fabulous, (g) stray dogs, (h) included in the present classification, (i) frenzied, (j) innumerable, (k) drawn with a very fine camelhair brush, (l) *et cetera*, (m) having just broken the water pitcher, (n) that from a long way off look like flies.

And Foucault concludes by observing that

> In the wonderment of this taxonomy, the thing we apprehend in one great leap, the thing that, by means of the fable, is demonstrated as the exotic charm of another system of thought, is the limitation of our own.
>
> *(Foucault, 1970: XV)*

Linking patterns in the Décodex network

Now that, by means of visual exploration, we have defined a heterogeneous but hermeneutically robust partitioning of our network, we can use it as a basis for a statistical analysis. While praising the advantages of the visual interpretation, we are also aware that not all structural properties can be rendered visually. The direction of edges or the connection between different classes, in particular, is not easily read in network images. These questions, however, can be investigated by other means once the partitioning of the network has been defined.

Figure 20.9 shows the distribution of nodes in the regions identified in our final classification, to which we have added the 'satirical' websites (which we discussed earlier but are not included in Figure 20.8 for the sake of legibility), as well as 'other reliable' and 'other *un*reliable'. These two residual categories comprise together about one-fifth of the nodes of the network. This relatively high figure is not uncommon. Given the heterogeneity of the networks they work with, social scientists and journalists should aim at classifications that are robust and insightful (capable of delineating homogenous zones in the graph) rather than comprehensive.

Our empirical categories are powerful tools to unveil different linking strategies in the network. Figure 20.10 presents the links in the corpus aggregated by categories. As we can see, not all categories cite or are cited the same way. 'French national media' and 'platforms' are greatly cited and by various actors (their columns contain larger circles), while 'satirical' websites are scarcely cited (their column is almost empty). Platforms are not cited much, but

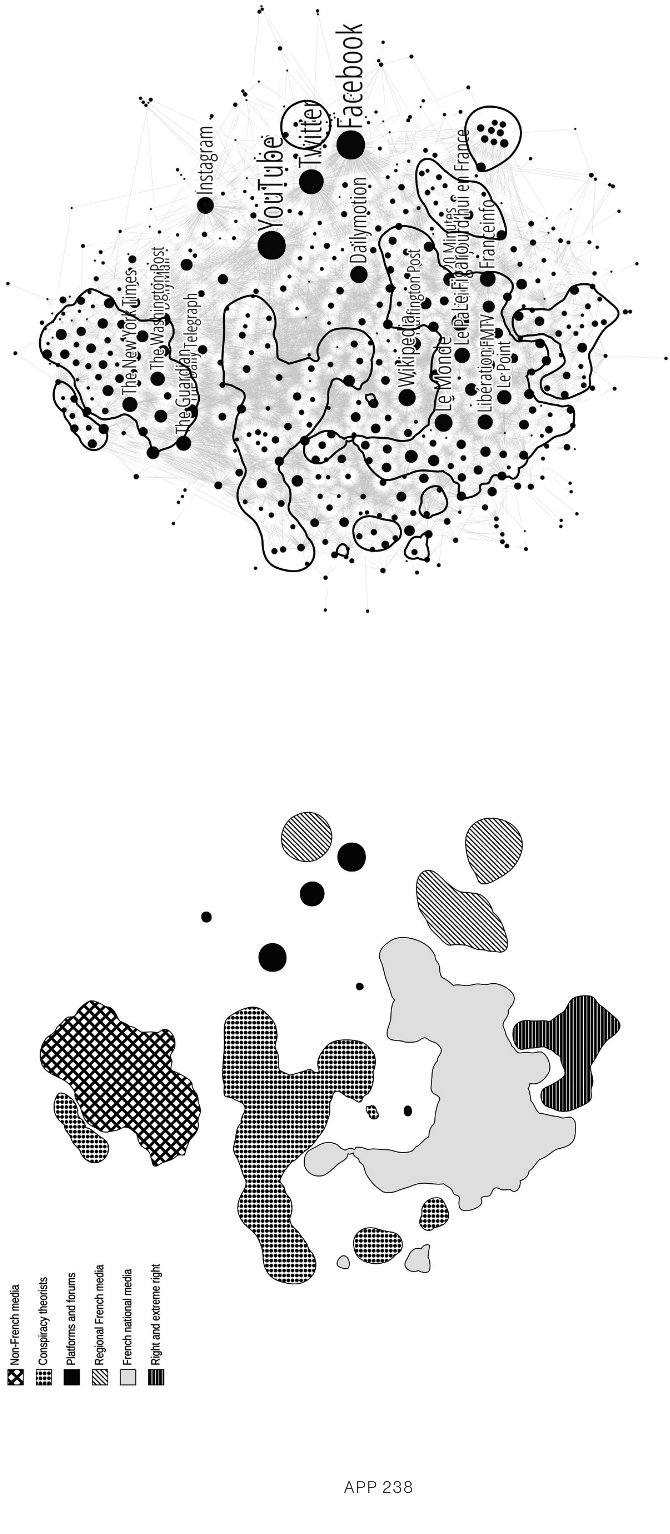


Figure 20.8 The heterogenous territories of the Décodex network

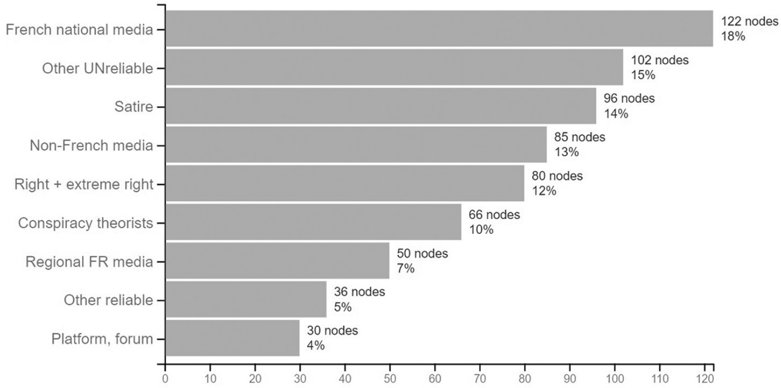


Figure 20.9 Distribution of the number of nodes per category

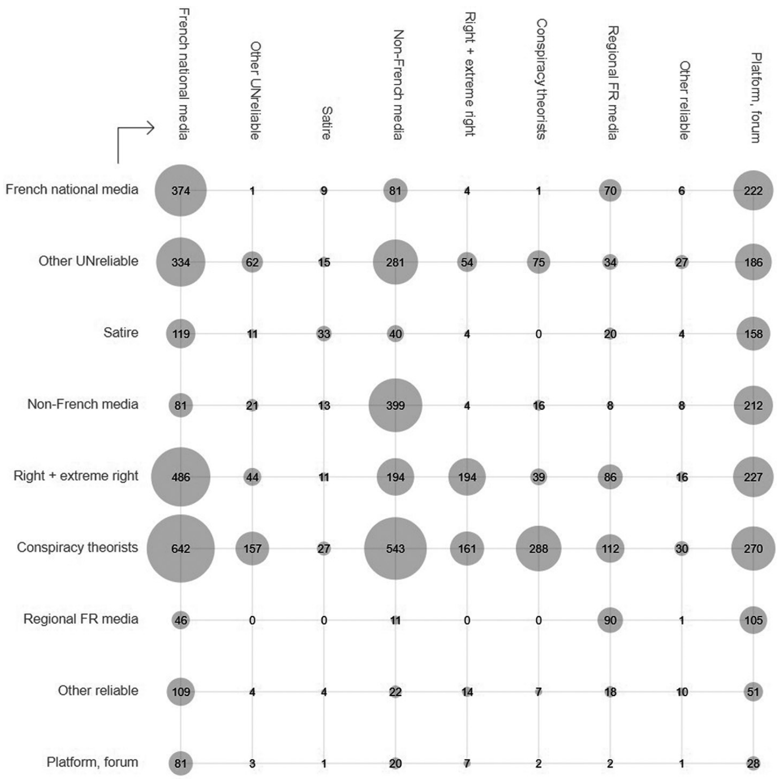


Figure 20.10 Connectivity between the categories of our final classification.
Rows convey how many times the nodes of a given category cite the nodes of other categories.
Columns convey how many times the nodes of a given category are cited by the nodes of other categories.

this is merely a consequence of our method since (as explained earlier) most of them had not been not crawled. 'Right-wing', conspiracy theorist and other '*un*reliable' websites are, on the contrary, the origins of the highest number of citations and, very interestingly, they seem to favor 'reliable' sources over 'unreliable' ones. As expected, the reliable websites do not link back to them, and this asymmetry reveals an important hierarchy (see Figures 20.11 and 20.12). To investigate this linking pattern, we will compare the incoming and outgoing links of some of the most interesting categories.

This kind of hierarchical structure is common on the web and has been explained as a consequence of preferential attachment (Barabási and Albert, 1999): actors tend to link to other websites that they perceive as higher in the hierarchy and avoid linking to those that they perceive as lower. This style of preferential attachment whereby smaller actors link to establishment actors without reciprocation of the linking act has elsewhere been called "aspirational linking" (Rogers, 2013). Links in a network do not always produce a hierarchy of categories, but this behavior does. This linking pattern and the way it fits our empirical categories may suggest an alternative way to characterize the trustworthiness being investigated by *Le Décodeurs*: reliable sources are cited by all types of websites, while unreliable sources are only cited by few other types (if any).

This observation is in many ways at odds with what is often affirmed about the 'post-truth era' in which we have supposedly landed. While fake news is said to leverage the horizontality of digital media to blur the boundaries between true and false, the linking patterns of the French information spheres suggest a different picture. Despite their different ideological leanings, all websites agree on the overall hierarchy of reliability by citing in one sense and not in the other.

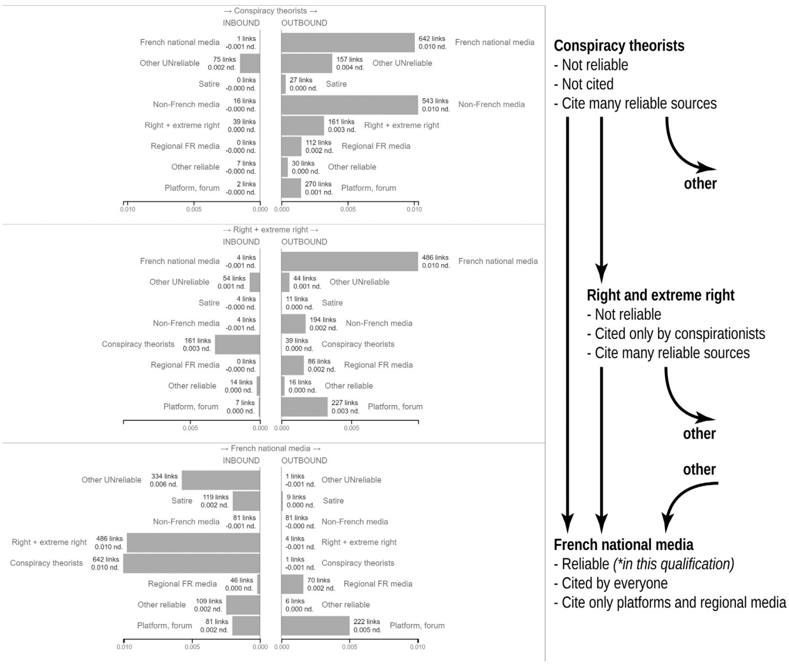


Figure 20.11 Hierarchical structure in the corpus, based on our final categories. Black arrows on the right side summarize the links structure between these categories.

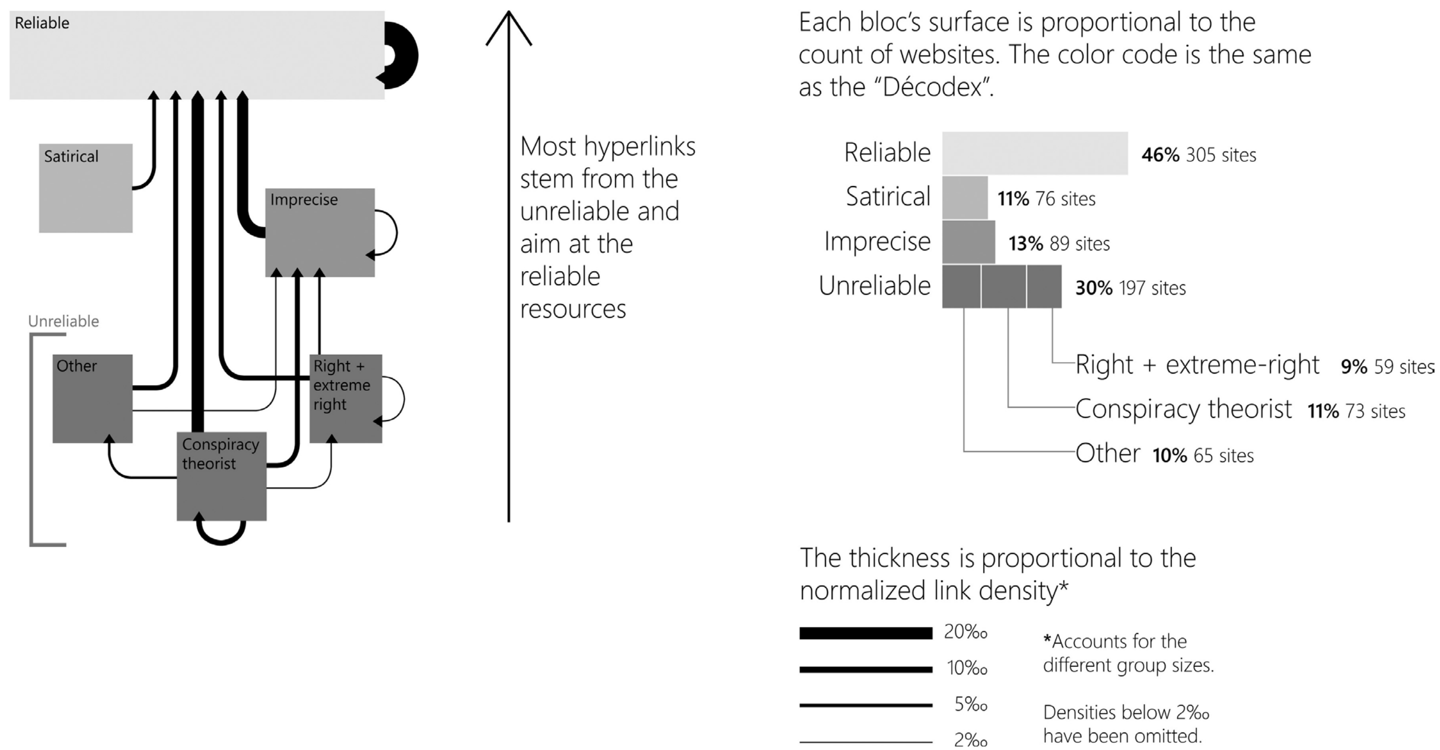


Figure 20.12 Simplified version of the statistical analysis presented in figure 20.11

The 'right-wing' websites, for example, try to blur the lines by citing both their peers and more reliable sources, but they also try to draw a line between them and the even less reliable 'conspiracy theorist' websites. Whatever its position in the pyramid of hyperlinking, every actor tries to improve its situation by linking upwards to authorities above and not linking to less reputable websites below, thus reinforcing the hierarchy.

Conclusion

This chapter discussed the visual exploration of networks with the aim of improving the understanding of one of the dominant visual-analytical forms of our digital age – the network diagram – and its potential role in relation to the study and practice of digital journalism. Drawing on graph semiotics and traditional cartography, this chapter proposed a model whereby the interpretation of network topology, with its regions, paths, cores, and peripheries, is guided by three visual variables: position, size, and hue. The process that we described is one that emphasizes the exploratory and iterative character of the investigation. While it seemed counterintuitive at first, we emphasized that in order to surface the multiple logics that play out in the structure of a network graph, analysis should not limit itself to one classificatory principle. Multiple heterogeneous criteria of classification are often necessary to characterize the topology of a network map. Finally, we advocated for mixing methods, complementing visual network exploration with statistical analyses in order to further characterize network properties.

Through the case study of French media hyperlink map, we tried to show how the visual exploration of networks reveals new angles that other analyses may leave unexplored. In this case, the chapter illustrated an alternative way to assess websites' reliability that complements the traditional fact-checking approach of qualifying content with an examination of the linking patterns between different regions of the network as reputational markers (Rogers, 2013). In this analysis, we have thus combined the manual classification of reliability undertaken by *Le Monde's* journalists with the standing of a source according to the hyperlinks that it receives and gives. This approach enabled us to bring fresh findings to current debates around fake news. In spite of the proliferation of fabricated content of various shades, reputation hierarchies on the web seem to be maintained (at least to some extent), as fake and hyper-partisan sites deploy aspirational hyperlinking styles that favor, perhaps surprisingly, authoritative sources.

Further reading

Interested readers can find complementary discussions of the use of networks in journalism by the same authors in "How to Tell Stories with Networks: Exploring the Narrative Affordances of Graphs with the Iliad" (2016, in M. T. Schäfer & K. van Es eds., *Datafied Society*. Amsterdam: University Press) and "Narrating Networks: Exploring the Affordances of Networks as Storytelling Devices in Journalism" (2017, *Digital Journalism*, 5:6, pp. 699–730). A more advanced discussion of the mathematics of graph visualization can be found in Freeman, L. C. (2009) "Methods of Social Network Visualization." In R. A. Myers (Ed.), *Encyclopedia of Complexity and Systems Science*, Berlin: Springer and in Liotta, G. (Ed.). (2004) Graph Drawing 11th International Symposium, Berlin: Springer.

References

Barabási, A. L. and Albert, R. (1999) "Emergence of scaling in random networks." *Science*, 286(5439), 509. Retrieved from www.sciencemag.org/cgi/content/abstract/sci;286/5439/509

Baruch, J. and Vaudano, M. (2016, April 8). "'Panama papers': un défi technique pour le journalisme de données." *Le Monde*. Paris. Retrieved from http://data.blog.lemonde.fr/2016/04/08/panama-papers-un-defi-technique-pour-le-journalisme-de-donnees

Behrens, J. T. and Chong-Ho, Y. (2003) "Exploratory data analysis." In I. B. Weiner (ed.), *Handbook of Psychology*. London: Wiley (pp. 33–64). doi:10.1002/0471264385.wei0202

Bounegru, L., Gray, J., Venturini, T. and Mauri, M. (2017) *A Field Guide to Fake News*. Retrieved from fakenews.publicdatalab.org

Bounegru, L., Venturini, T., Gray, J. and Jacomy, M. (2016) "Narrating networks: Exploring the affordances of networks as storytelling devices in journalism." *Digital Journalism*, 5(6), 699–730.

Bowker, G. C. and Star, S. L. (1999) *Sorting Things Out: Classification and Its Consequences* (Inside Technology S.). Cambridge, MA: The MIT Press.

Burt, R. S. (1995) *Structural Holes: The Social Structure of Competition*. Cambridge MA: Harvard University Press. Retrieved from http://books.google.com/books?id=E6v0cVy8hVIC&pgis=1

Foucault, M. (1970) *The Order of Things*. New York, NY: Pantheon Books.

Freeman, L. C. (2000) "Visualizing social networks." *Journal of Social Structure*, 1(1).

Früchterman, T. M. and Reingold, E. M. (1991) "Graph drawing by force-directed placement." *Software: Practice and Experience*, 21(November), 1129–1164. Retrieved from http://onlinelibrary.wiley.com/doi/10.1002/spe.4380211102/abstract

Girard, P. (2011) "HyperText Corpus Initiative: How to help researchers sieving the web?" In Using Web Archives (ed.), *Out of the Box Conference*. Den Haag, The Netherlands: IIPC.

Girard, P., Jacomy, M., Baneyx, A. and Venturini, T. (2012) "The Hypertext Corpus Initiative: methods and tools for Social Sciences to build corpus from the web." In *Websites as Sources*. Luxembourg, Luxembourg: CECV.

Jacomy, M., Girard, P., Ooghe, B. and Venturini, T. (2016) "Hyphe, a curation-oriented approach to web crawling for the social sciences." *International AAAI Conference on Web and Social Media* (pp. 595–598). Retrieved from https://hal.archives-ouvertes.fr/hal-01293078/

Jacomy, M., Venturini, T., Heymann, S. and Bastian, M. (2014) "ForceAtlas2, a continuous graph layout algorithm for handy network visualization designed for the gephi software." *PLoS ONE*, 9(6), e98679. doi:10.1371/journal.pone.0098679

Jensen, P., Morini, M., Karsai, M., Venturini, T., Vespignani, A., Jacomy, M., . . . Fleury, E. (2015) "Detecting global bridges in networks." *Journal of Complex Networks*, cnv022. doi:10.1093/comnet/cnv022

Lynch, K. (1960) *The Image of the City*. Cambridge, MA: The MIT Press. Retrieved from http://books.google.com/books?hl=it&lr=&id=_phRPWsSpAgC&pgis=1

Marres, N. and Rogers, R. (2005) "Recipe for tracing the fate of issues and their publics on the web." In B. Latour and P. Weibel (eds.), *Making Things Public: Atmospheres of Democracy*. Cambridge, MA: The MIT Press (pp. 922–935).

Moreno, J. (1953) *Who Shall Survive?* (2nd ed.). New York, NY: Beacon House Inc.

The New York Times. (1933, April 3) "Emotions mapped by New Geography." *The New York Times*.

Noack, A. (2009) "Modularity clustering is force-directed layout." *Physical Review E*, 79(2). doi:10.1103/PhysRevE.79.026102

Rogers, R. (2013) *Digital Methods*. Cambridge, MA: The MIT Press.

Tukey, J. W. (1977) *Exploratory Data Analysis*. Reading, MA: Addison-Wesley.

Turnbull, D. (2000) *Masons, Tricksters and Cartographers*. London: Routledge.

Venturini, T., Jacomy, M. and Jensen, P. (forthcoming) "What do we see, when we look at networks. towards a positive measure of spatialisation quality for force-driven network Layouts." Forthcoming.

APPENDIX D. WHAT DO WE SEE WHEN WE LOOK AT NETWORKS?

The document presented here is the first revision after peer-review, as sent to the journal *Big Data & Society*, 2020-08-19.

Venturini, T., Jacomy, M. and Jensen, P. (under review in Big Data & Society) 'What do we see when we look at networks: Visual network analysis, relational ambiguity and force-directed layouts'.

What do we see when we look at networks
Visual Network Analysis, relational ambiguity and force-directed layouts

It is increasingly common in natural and social sciences to rely on network visualizations for the exploration of relational datasets and the illustration of findings. Such practices have been around long enough to prove that scholars find it useful to project networks in a two-dimensional space and to use their visual appearance as a proxy for their topological features. Yet these practices remain based on intuition, while the foundations and limits of this type of exploration are still implicit. To fill this lack of formalization, this paper offers an explicit documentation of the kind of *visual network analysis* (VNA) allowed and encouraged by *force-directed layouts*. It provides guidelines on how to make networks readable and interpret their visual features. It discusses how the inherent ambiguity of network visualizations can be tamed and exploited for exploratory data analysis. Acknowledging that vagueness is a feature of many relational datasets in the humanities and social sciences, the paper contends that visual ambiguity, if properly interpreted, can be an asset for the analysis. We propose a detailed example of VNA on Jazz music, to situate VNA in relation to other forms of network analysis. Finally, since the practice of VNA calls for an assessment of layout quality, we offer two simple experiments aiming at operationalizing such an assessment. We discuss why these experiments are only partially successful, and we propose further steps towards a metric of spatialization quality.

Introduction

There is no point in denying it, networks are not only mathematical but also visual objects. If network computation has existed since the 18th century, the last couple of decades have seen the rise of network *visualization* as a tool of scientific investigation (Freeman, 2000, Correa & Ma, 2011). This visual renaissance is particularly noticeable in digital humanities and social sciences – where the increasing availability of relational datasets has fuelled the interest for graph charts – but it has also touched other disciplines such as ecology, neuroscience, and genetics. In general, it has become common to illustrate social relations, economic fluxes, linguistic co-occurrences, protein interactions, neuronal connections and many other relational phenomena as *points-and-lines charts*.

The function of such charts, however, is often unclear. While network visualizations are regularly exhibited as tangible evidence of findings, they are generally left out of the actual demonstration (which relies instead on calculations and metrics). Network charts are embraced for their insights but distrusted as scientific proofs because of their distinctive ambiguity. Unlike a bar chart or a scatter plot, a points-and-lines chart is not simply shaped by its rules of construction. Instead, its shape depends on the relationships between its elements in ways that cannot be straightforwardly recognized (outside trivially simple networks such as trees, stars or grids). Graphs are multidimensional mathematical objects and visualization squeezes them in a two-dimensional space, flattening but not reducing their complexity. No wonder that scientists are wary of graph charts. And no wonder that most literature on network visualization (see, for instance, the works of the community of the *Symposium on Graph Drawing and Network Visualization*) has strived to reduce visual ambiguity by tweaking points-and-lines charts (Dunne & Shneiderman, 2009; Shneiderman & Dunne, 2013), transforming the data (Nick *et al.*, 2013; Epasto & Perozzi, 2019) or dismissing this type of visualization altogether (von Landesberger *et al.*, 2001; Aris & Shneiderman, 2007; Henry et al. 2012).

This paper proposes an alternative approach: instead of trying to overcome the ambiguity of points-and-lines charts, it considers it productively. Not only as a burden, but also as an asset. The same ambiguity that makes network charts unfit for hypothesis confirmation, we contend, makes them useful for exploratory data analysis. This is particularly true for the network of hundreds or thousands of nodes, often found in social and biological phenomena. Alongside the metrics and models typically employed by network science and social network analysis, there exists a practice of *visual network analysis* (VNA), that allows to explore the richness of relational datasets and exploit (rather than reduce) their inherent ambiguity (Decuypere, 2020). This practice is widespread but remains mistrusted because of its lack of documentation (Jokubauskaite, 2018). The working hypothesis of this paper is that, by making explicit the heuristic bases of VNA and investigating its specific way of dealing with relational ambiguity, we can build trust in this practice and make it even more useful as a technique for exploratory data analysis.

To address this hypothesis, this paper offers an account of VNA practices and an explicitation of its foundations. Because this technique is yet unsettled, we will alternate theoretical and practical considerations and unfold our argument through examples, using the software Gephi (http://gephi.org, Bastian et al., 2009, but see Cherven, 2015 or Khokhar, 2015 for a more how-to introduction to Gephi).

(1) We start by reviewing the standards of points-and-lines charts and retracing their development in the history of force-directed layouts. (2) We propose a detailed illustration of how to visualize networks using these tools in ways that respect their ambivalence and exploit their heuristic power. (3) We situate VNA by discussing the kind of information that it delivers and the way in which it preserves ambiguity. (4) We conclude by sketching a formal analysis of the assessment of force-directed layouts.

1. Force-directed layouts and the practice of visual network analysis

The heuristic value of network visualizations was first noticed in the second half of the 20th century by the early school of *social networks analysis* or SNA (Scott, 1991, Wasserman & Faust, 1994). Jacob Moreno, founder of such approach, explicitly affirmed that “the expression of an individual position can be better visualized through a sociogram than through a sociometric equation” (Moreno, 1934, p. 103).

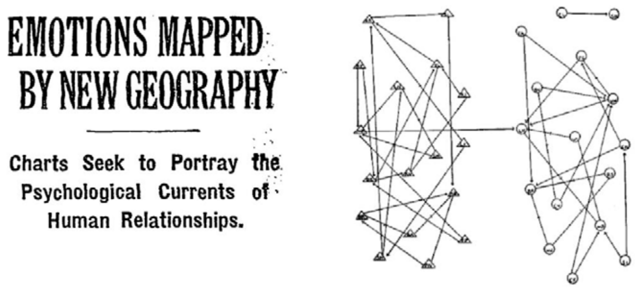


Figure 1. Sociogram representing friendship among school pupils
(original title and image accompanying Jacob Moreno’s interview by the New York Time, 1933)

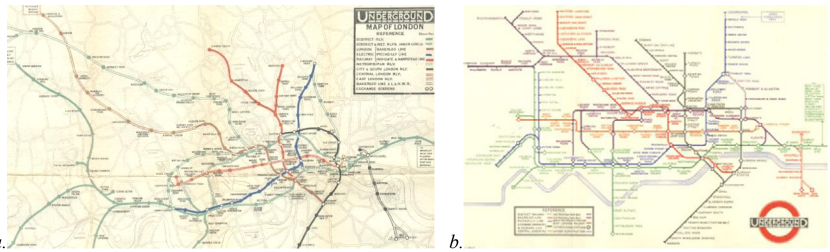
Working on their sociograms, Moreno and his disciples set the standards for the visualization of networks (Freeman, 2000 & 2009). Their point-and-line approach has been so successful that it has become the *de facto* standard of network drawing. So much, in fact, that it now feels useless to specify that in these charts the points represent the nodes and the lines represent the relationships connecting them, although this choice is by no means evident (in matrices, for instance, points indicate connections while nodes are rendered as rows and columns).

But standardisation has gone further. Even within the *points-and-lines* family, diversity has been progressively reduced and today most networks visualizations abide by three unwritten principles according to which nodes are (1) positioned according to their connectivity; (2) sized proportionally to their importance; and (3) coloured or shaped by their category. Together these principles constitute the foundations of VNA, as discussed in the next section. For the moment, let us consider the first one, which is the most specific to this technique but also the most problematic.

The cornerstone of VNA is the use of "force-directed layouts" to draw networks in a two-dimensional space (Battista *et al.*, 1999). These algorithms may be implemented according to different recipes but they all rest on the same physical analogy: nodes are charged with a *repulsive force* driving them apart, while edges introduce an *attractive force* between the nodes that they connect. Once launched, force-vectors vary the position of nodes trying to balance the repulsion of nodes and the attractions of edges. At equilibrium, force-directed layouts produce a *visually meaningful* disposition of nodes, where nodes that are more directly or indirectly related *tend to* be closer.

This technique to visualize graphs has become so common that we often fail to notice its accomplishment. Force-directed layouts do not just project networks in space – they create a space that would not exist without them. This is why this process is better called "spatialization" rather than "visualization." Spatialization creates a space in which the multidimensionality of networks can be flattened, in a process of "graph embedding" (Yan *et al.*, 2007) that has applications even outside visualization. Spatialization creates a space that retains key properties of a network.

To understand this feat, consider the plan of an underground, rail or bus system. Strictly speaking, most of these plans are *not* geographical maps – they are not drawn by setting up a system of coordinates *first* and *then* placing the stations according to their coordinates. Instead, they are charts in which proximity represents connectivity rather than spatial distance. Introduced in 1993 for the London tube by Harry Beck (Hadlaw, 2003), this design technique has become a standard for public transportation systems. Compared to geographic maps, this type of representation is more focused on the information needed by users (which lines should I take to go from A to B and where should I change train) while remaining readable according to the visual conventions of geographic charts. Not a little advantage given the huge efforts invested to build and spread the conventions of cartographic mapping (see, among others, Turnbull, 2000).



a. *b.*

Figure 2 London Underground map (a) before and (b) after Harry Beck redesign (1933)

A similar advantage explains the appeal of force-directed layouts: they allow reading networks *as* geographical maps, despite the fact that network space is a consequence and not a condition of elements' positioning. In a force-spatialized visualization there are no axes and no absolute coordinates, and yet the relative positioning of nodes is relationally significant. One can compare distances, gauge centres and margins, estimate density and often bring home interesting observations.

These insights, however, are not always easy to obtain. The fact that network charts can be read through an intuitive analogy with geographical maps does not mean that their messages are easy to interpret. Point-and-line charts resemble more to orographic maps than to political maps: their features are blurred and overlapping as plains and chains of mountains rather than clearly defined as geopolitical borders. Force-directed visualizations are evocative rather than descriptive and making sense of their uncertain patterns is a matter of craft as much as of science. To observe relational structures in the image of a network, one has to know not only where to look, but also how to make such structures visible. This is why the next section discusses *combinedly* how to read networks and how to make their visual ambiguity readable.

2. How to read networks and make them legible

The "jazz network" graph

Most testbed networks in graph litterature are too small to exemplify VNA. It is easy to observe relational structures with a few hundreds of nodes, but we wanted to show that VNA can be applied to networks with thousands of nodes. Inspiration came from a famous network of jazz musicians created by Gleiser & Danon (2003). As observed by McAndrew et al. (2014), "as a music form, jazz is inherently social" and thus particularly propitious to network analysis (see Sonnett, 2016 and Vlegels & Lievens, 2017 for others network of musical genres). Yet, the original jazz network contains only 1,473 nodes and is limited to bands performing between 1912 and 1940. We thus produced an updated and expanded jazz network (available at github.com/tommv/ForceDirectedLayouts):

- We used Wikidata.org to extract
  1. The 6,796 instances of "human" and the 976 instances of "band" with "genre = jazz" in English Wikipedia. For each, we collected (when available):
     - "birth year" or "inception" date
     - "citizenship" and "country of origin" (when multiple, we kept the first one).
     - "ethnic group" and "gender."
  2. The 53 jazz "subgenres" and the 396 "record labels" associated with individuals and bands.
- We used the Hyphe web crawler (Jacomy et al., 2016; Ooghe-Tabanou et al., 2018) to visit all the pages and extract the hyperlinks connecting them.
- From the resulting graph
  - We removed all the edges that did not have an individual or a band as one of their vertices.
  - We kept only the largest connected component, obtaining a network of 6,381 nodes (5,396 individuals, 589 jazz bands, 346 record labels and 50 subgenres) and 85,826 edges.

Positioning nodes

We argued above that, in spatialized networks, closer nodes *tend to be* more directly or indirectly associated. Caution is crucial, because no strict correlation exists between the geometric distance in the layout and the mathematical distance in the adjacency matrix. We will discuss this fundamental ambiguity of VNA in sections 3 and 4. For the moment, let us consider its practical consequence: in VNA, rather than considering the exact position of nodes or the precise distance between node pairs, we are concerned with their general grouping – the *visual density of nodes* and its variation.

In a continuum that goes from a set of disconnected nodes (a "stable") to a fully connected clique, the structure of a network is revealed by the lumps and the hollows created by the uneven distribution of relations. Since force-directed layouts would represent both stables and cliques as circles filled with nodes at the same distance, everything that departs from this disposition indicates the existence of some relational structure. When analyzing a spatialized network, therefore, we should look for shapes that are not circular – which indicate polarization – and differences in the density of nodes – which indicate clustering.

Don't be too quickly discouraged if your network looks like an amorphous tangle (a "hairball"). Legibility depends crucially on the spatialization algorithm and its settings. Though all force-directed algorithms rely on similar systems of forces, they differ for the way in which they handle computational challenges (eg. the optimisation of calculations) and visual problems (eg. the balance between compactness and legibility). What appears as a homogenous distribution can sometimes derive from unfortunate layout choices.

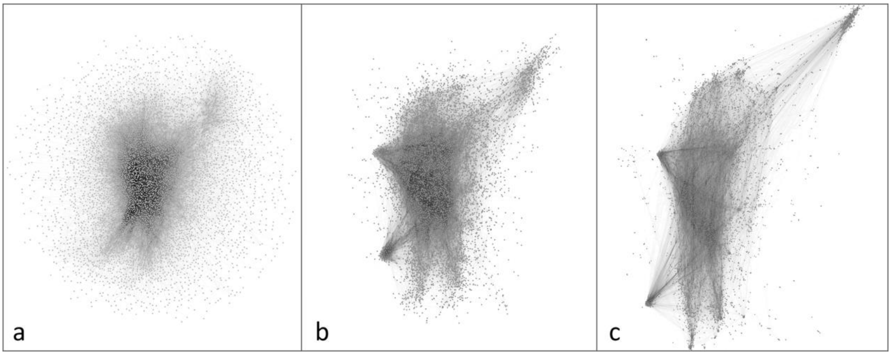


Figure 3 *The "jazz network" spatialized (a) with the algorithm proposed by Fruchterman & Reingold, 1991, (b) with ForceAtlas2 (with default parameters) and (c) with ForceAtlas2 with tweaked parameters for "LinLog mode" and "gravity."*

Figure 3 shows that our network of individuals and bands (for the moment, we filter out subgenres and record labels) displays less local gatherings of nodes when spatialized with Früchterman & Reingold (1991) layout, than when ForceAtlas2 is used (Jacomy et al., 2014), particularly if the "LinLog mode"[1] is used and "Gravity"[2] is set to zero. As it is thus impossible to suggest a "catch-all setting" (e.g. *LinLog mode* and *zero gravity* tend to highlight clusters, but they also produce a more scattered layout and take longer to converge to equilibrium), recursively adjusting the spatialization settings to the analyzed network is crucial to make the relational structures visible (just as choosing the right chart and tweaking its properties is essential to make sense of a large data table).

Sizing nodes and labels

After having positioned the nodes to reveal polarization and clustering, we still have to make sense of what we see. To do so, VNA draws on two other visual variables (Bertin, 1967): size and colour. The degree (number of edges connected to a node) or the in-degree (number of *incoming* edges) are classic choices for sizing nodes, as they represent the most literal translation of visibility in networks. Being entirely relational, the degree can be computed for any network. Yet, when available, other non-relational variables could be equally interesting. For instance, we can change the size of nodes of our networks according to the number of visits received in 2017 by each Wikipedia page.

[1] The "LinLog mode" parameter tweaks the way in which distance is factored in the computation of attraction and repulsion forces. In default ForceAtlas2, both forces are linearly proportional to the distance (with inverted proportionality for attraction). However, using a repulsion force logarithmically proportional to distance (ie. the "LinLog mode") renders clusters more visible.

[2] "Gravity" is a generic force that pulls all nodes toward the centre. While it avoids disconnected nodes to drift away from the rest of the network, such a gravitational force interferes with the attraction-repulsion balance of force-directed layouts (an excessive gravity packs all the nodes in the centre).

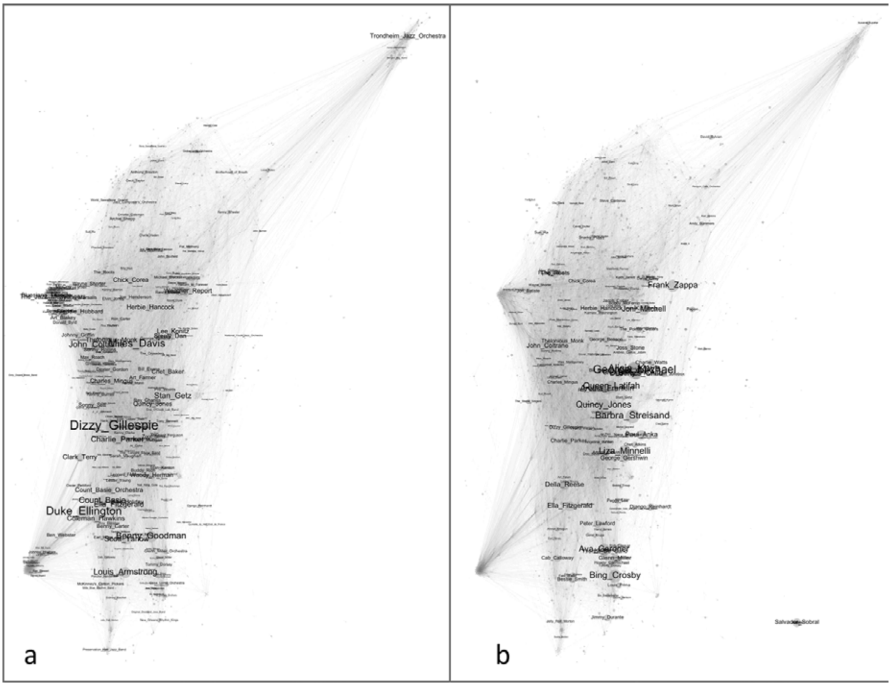


Figure 4 *The "jazz network" with nodes and labels sized according to (a) in-degree of the nodes; (b) number of page views of the related pages in the English Wikipedia.*

Note that in figure 4, we have varied not only the size of the nodes, but also of their label (and deleted all the smallest labels). This foregrounding operation is crucial, as inspecting hundreds or thousands of nodes is clearly not an option. Observing the labels of the most visible nodes, we can start to make sense of the shape of our network. Comparing the two images in figure 4, we notice that nodes with high in-degrees tend to be on the left, while nodes with high pageviews on the right. Also, high in-degree nodes are famous jazzmen (the top-five being Dizzy Gillespie, Duke Ellington, Miles Davis, Benny Goodman and John Coltrane), while high pageviews nodes are pop-culture celebrities (top-five: George Michael, Alicia Keys, Barbara Streisand, Liza Minelli, Bing Crosby). This reveals a left-right spreading corresponding to a more or less pure jazz lineage. This left-right separation, however, is not the most important. Indeed, the network appears to stretch vertically more than horizontally, as if pulled by opposite poles – we refer to this visual feature as polarization.

Colouring nodes

To investigate the vertical polarization, we use a third visual variable: colour. Noticing at the bottom names such as Louis Armstrong, Duke Ellington and Bing Crosby and at the top Chick Corea, Weather Report and Frank Zappa, we can hypothesize that the vertical polarization is connected to time. In our dataset, we have the year of birth and of inception for individuals and bands and we can project them on the network using a scale going from green (for the oldest actors) to magenta (for the most recent).

While the separation is not complete[3], figure 5a seems to confirm our hypothesis that the vertical polarization corresponds to time.

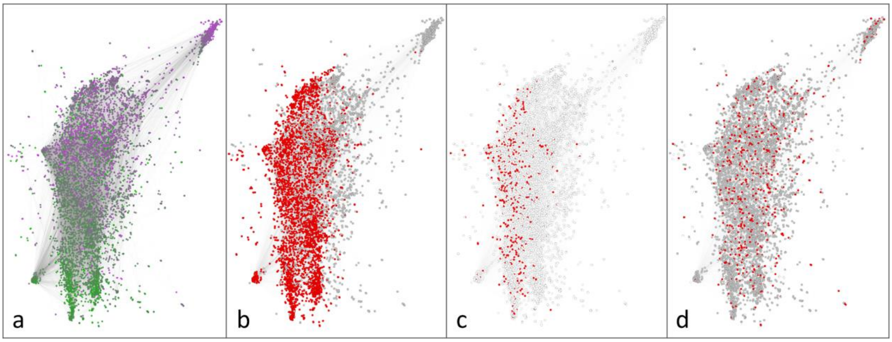


Figure 5 The "jazz network" with nodes coloured according to
(a) the year of their birth or inception (from green for older individuals and bands to magenta for newer);
(b) their nationality (red for US, grey for all other countries, white for not available);
(c) their ethnic groups (red for African American, grey for other ethnic groups, white for not available);
(d) their gender (red for women, grey for men, white for not available or others)

Figure 5b and 5c are dedicated respectively to nationality and ethnic group and confirm the interpretation that the horizontal polarization may be connected to the "purity" of the jazz genre (most non-American actors tend to be on the right, while most African American are on the left). To be sure, not all variables will turn out to be connected to visual structures. Figure 5d, for example, shows how men and women are mixed in our network, producing no relational fracture.

Using force-directed spatialization to determine the position of nodes and size and colour to project variables on the layout, we identified two sources of polarization: primarily time, stretching the network vertically, and secondarily "genre purity," stretching it horizontally. These, however, are not axes. Force-vector algorithms are not dimensionality reduction techniques like correspondence analysis (Ter Braak, 1986; de Nooy, 2003) and do not create a space of coordinates. In force-driven placement algorithms, space is isotropic (the same in every direction) and polarization is generally not coherent across different clusters: the same variable might spread left-to-right in one cluster and top-down in another (Boullier, Crépel & Jacomy, 2016).

Naming poles and clusters

In VNA, visual clusters are defined as regions where many nodes flock together, surrounded by areas with sparser node density (the "structural holes" of Burt, 1995). In our network, the only easily identifiable cluster is the one at the top right, which contains the Scandinavian musicians of the *Trondheim Jazz Orchestra*. The other clusters are more difficult to identify and highlighting them will require using two advanced techniques.

The first is performed in a tool called Graph Recipes (tools.medialab.sciences-po.fr/graph-recipes) through a script (available at github.com/tommv/ForceDirectedLayouts) that transforms a network chart in a density heatmap. The second characterizes the different areas of the network through a set of "qualifying nodes" (in our example, jazz subgenres and record labels) and a "double spatialization". We

[3] Part of the mixing is due to the fact that, while the inception date corresponds directly to the moment in which bands started to be active on the jazz scene, this is not the case for the birth date, which is obviously offsets by several years. However, as our dataset spans over almost 150 years (the earliest date being 1870 and the latest 2014) the distribution of the two timescale remains consistent in the network and does not require correction.

first spatialize the network with only bands and individuals and freeze the position of these nodes. We then add the subgenres and record labels and run the spatialization again but only these qualifying nodes[4]. The qualifying nodes can then be used as labels for the clusters in which they end up being located.

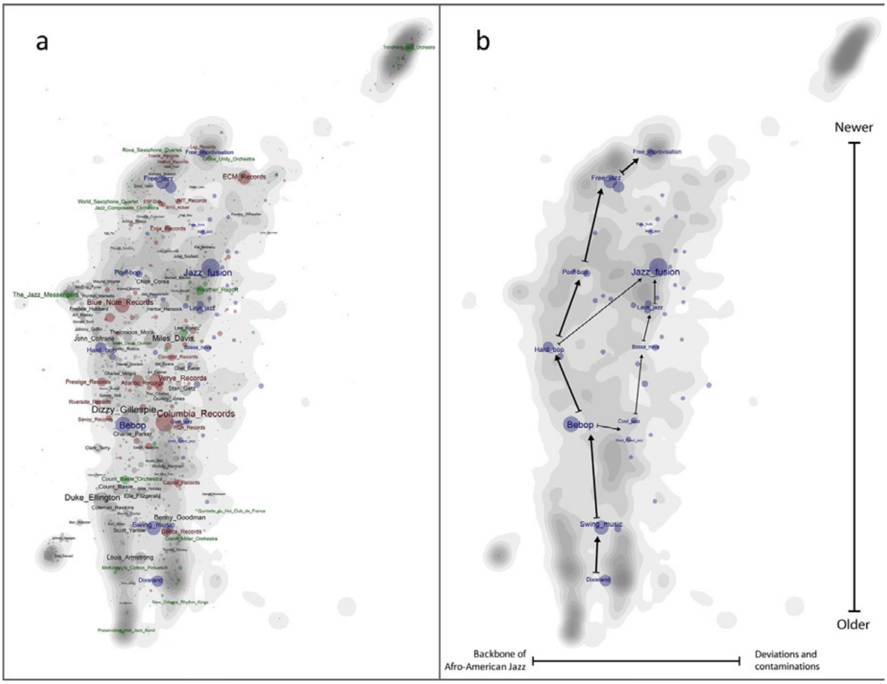


Figure 6 *The "jazz network" with (a) the labels of the most salient node of each type (grey for individual, green for bands, blue for subgenres and red for record labels) and (b) the identification on the structure of the network in terms of the evolution of the jazz musical language.*

Qualitative interpretation of the position of nodes and clusters

Now that we finalized our visualization, we can make sense of its overall structure and of the position of its most important nodes[5] – it is an advantage of VNA that it allows observing global patterns and local configurations in the same visual space (ANONYMIZED, 2012). In figures 6 and 7, one can observe (from the bottom to the top) the development of the jazz musical language. This evolution occupies the left of the image. It starts from *dixieland* and *swing music* and progresses to *bebop*, *hard bop*, *post bop* and finally to *free jazz* and *free improvisation*. From this backbone of Afro-American jazz, deviations (such as the *cool jazz* and *west coast jazz*) and contaminations with other genres (such as *bossa nova*, *latin jazz* and later *jazz fusion*) branch to the right of the chart.

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[4] A last detail: though the Wikipedia pages related to the subgenres and record labels have hyperlinks connecting them, we removed these edges from our network, so that the qualifying nodes are only positioned according to their connections to the primary nodes (and not between themselves).

[5] We thank Emiliano Neri, whose jazz expertise was instrumental in this analysis.

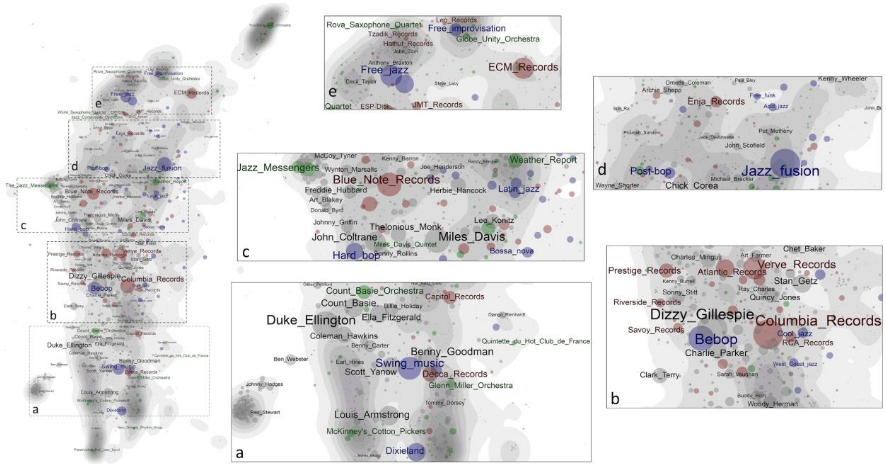

Figure 7 Mosaic providing a zoom on the different regions of the "jazz network"

[7.a] The bottom of the image corresponds thus to the early years of the genre and is marked by Decca Records and Capitol Records, both particularly active in the 1930s and 1940s. The region of *dixieland* and *swing music* is split in two parallel clusters (already identified by Glaiser et al., 2003): to the right, the "white big bands" around *Tommy Dorsey*, *Glenn Miller* and *Benny Goodman*; and to the left the "black big bands" around *Louis Armstrong*, *Count Basie* and *Duke Ellington*. This last bandleader also is at the origin of the smaller cluster to the bottom left, constituted by the members of its orchestra. Vocalists such as *Ella Fitzgerald* and *Billie Holiday* are positioned toward the centre because of their numerous collaborations. To the right, is *Django Reinhardt*, whose isolated position is justified by his living in Europe.

[7.b] Moving up toward *bebop*, new record labels emerge such as *Verve* and *Columbia*. Very close to the node representing *bebop*, one can find the trumpeter *Dizzy Gillespie* and the saxophonist *Charlie Parker*, who were among the most influential artists of this new style, and the vocalist *Sarah Vaughan* who collaborated with both. In a bridging position are *Woody Herman* and *Clark Terry*, whose long careers spanned between *swing* and *bebop*.

[7.c] Moving upward, the increasing dispersion of nodes illustrates the growing diversification of jazz in the 1950s. On the left of the chart, *bebop* evolves into *hard bop*, thanks to the *Blue Note* record label and to musicians such as *Charles Mingus*, *Sonny Rollins*, *Thelonious Monk* and *Art Blakey*. This last bandleader is at the origin of the *Jazz Messengers* ensemble, which creates a little cape on the left of the map and incubated talents such as *Freddie Hubbard*, *McCoy Tyner* and *Wynton Marsalis*. On the right of the chart, *west coast jazz* and *cool jazz* evolve through the contamination with styles from Latin America, giving birth to *bossa nova* and *latin jazz*, popularized in the US by *Stan Getz* and *Quincy Jones. John Coltrane* and *Miles Davis* occupy the centre of this region (and of the whole graph) for the crucial role they played in bridging all these experiences.

[7.d] In the 1960s, the contaminations on the right of the chart turn toward rock and funk music originating the *jazz fusion*. Musicians such as *Chick Corea*, *Herbie Hancock*, *John Scofield* and *Pat Metheny*, as well as the group *Weather Report*, play a crucial role in this experience. At about the same time, and with connections assured by artists such as *Joe Henderson* and *Michael Brecker*, *hard bop* develops into *post-bop* thanks to musicians such as *Wayne Shorter* and *Elvin Jones*.

[7.e] In the 1970s and 1980s, experiences of radical improvisation conquer the avant-garde, giving birth to *free jazz* and *free improvisation*. Initiated by musicians such as *Sun Ra*, *Cecil Taylor*, *Archie Shepp* and *Ornette Coleman*, this style is developed by *Anthony Braxton*, *John Zorn*, *Evan Parker* and many others. Interestingly, this genre seems to be supported particularly by European record labels such as *JMT* and *ECM*. This last record label is also the bridge that connects the cluster of the Scandinavian jazz to the rest of the maps.

3. What type of analysis is visual network analysis?

Diagrammatic vs topological visualizations

The jazz network example provides an illustration of the specific sense in which VNA is a method for *reading* relational ambiguity. While force-directed algorithms have long been employed to improve networks legibility, the meaning of this "legibility" has evolved over time. Historically, force-directed layouts were introduced to satisfy aesthetic criteria like "minimizing edge crossings" or "reflecting inherent symmetry" (Früchterman & Reingold, 1991; Purchase *et al.*, 1996; Purchase, 2002). We call this approach *diagrammatic* as in this perspective reading a network means following its paths as in a flow chart or tree diagram (Lima, 2014).

This approach, however, is only possible for small networks for the intricacy of visualizations grows so quickly that even graphs with a few hundreds of nodes are impossible to read in this way. This does not mean, however, that force-directed layouts lose their interest. Introduced for diagrammatic objectives, these layouts stuck for their capacity to make relational structures visible. When the balance of forces is reached, clusters *tend to* appear as denser gatherings of nodes; structural holes *tend to* look like sparser zones; central nodes move *towards* middle positions; and bridges are positioned *somewhat* between different regions. We call this second perspective *topological* as its objective is to turn topological structures into visual characteristics (see Grandjean & Jacomy, 2019 for an attempt at assessing such a correspondence).

Diagrammatic and topological perspectives coexist in practice and are often confused as some aesthetic features (eg. symmetry) may be desirable both *per se* and as a translation of topology. Nevertheless, the two approaches come from different traditions and have different aims – *graph drawing* is rooted in algorithmics and focuses on network paths, while *network visualization* stems from information design and is interested in relational structures. For instance, replacing edges with a density heat map (as we did in fig. 6) makes sense from a topological perspective because it helps reveal clusters but is absurd from a diagrammatic viewpoint for it defeats the objective of following the paths between nodes.

Ultimately, the two perspectives serve different needs. A diagrammatic stance suits small networks, whose configuration is simple enough to be qualitatively appreciated, while a topological attitude is more appropriate for larger networks, where pattern detection is preferred. This explains why, in the last few years, the attention of scholars has gradually shifted from the diagrammatic to topological approach. Diagrams, favoured in the early years of network visualization, are becoming obsolete when confronted to the growing size of relational datasets (Henry *et al.*, 2012). Reviewing an assessment of spatialization algorithms by Purchase *et al.* (1996), Gibson *et al.* (2013) note for instance:

> The type of tasks she [Helen Purchase] asked her users to complete… were finding shortest paths, identifying nodes to remove in order to disconnect the graph and identifying edges to remove in order to disconnect the graph … It is unclear as to if this type of accurate, precise measurements are a typical analysis tasks for graphs with hundreds or thousands of nodes …. If those kinds of tasks become infeasible due to the volume of nodes and edges then the better layouts should support the user for a different set of tasks … to support users in tasks concerned with overview, structure, exploration, patterns and outliers (pp. 27, 28)

Although both perspectives coexist in the literature, the topological visualization is underdiscussed. For instance, when Hansen et al. (2012) propose a model for network visualization, they rely on the popular "Netviz Nirvana", a set of four rules proposed by Dunne & Shneiderman (2009) to evaluate a layout's quality, which only comprises one topological criterion (the last one): "(1) Every node is visible; (2) For every node you can count its degree; (3) For every edge you can follow it from source to destination; (4) Clusters and outliers are identifiable." The topological perspective has been mentioned multiple times but has rarely been addressed directly until recently (see for instance Soni et al., 2018). Likewise, when Brandes et al. (2006) assess "the explanatory power of network visualization", they focus exclusively on visualizing centrality and prestige metrics, in line with the rationale of the tool *Visone* (Brandes & Wagner, 2004).

VNA and exploratory data analysis

In presenting our analysis of the jazz network, we have described the sequence of transformations imposed on our graph to make it readable. For the sake of simplicity, we presented this sequence as linear and orderly, as if we knew from the beginning how to stack its operations and set its parameters. Of course, this was not the case and our actual inquiry entailed many trials and errors, and a lot of backs and forth between different visual variables and their parameterization. At some point we even realized that our original data collection was flawed and had to be renewed (we initially treated ensembles as "qualifying nodes," while in the analysis their role turned out to be akin to that of musicians). This type or iteration is very common in VNA, which cannot be carried out without a continuous switch between data and visualization, zooming and panning, selecting and filtering.

VNA is in this sense a form of "exploratory data analysis" (Behrens & Chong-Ho, 2003). Introduced by John Wilder Tukey (1977), EDA covers all the operations that researchers carry out to make sense of their data before formulating clear hypotheses or findings (the so-called "confirmatory data analysis"). VNA is a form of EDA because, in contrast with most graph metrics, it conserves each node and edge as a separate element. This allows to interpret global patterns by observing single nodes (eg. when we relied on "subgenre nodes" to identify the clusters of our jazz networks) and conversely to appreciate single nodes by considering their position in the overall landscape (eg. the crossroad position of Coltrane and Davis).

The ability to maintain the singularity of nodes and edges, however, is paid for with the impossibility to use VNA on massive datasets. This explains why VNA is particularly popular as a way to analyze the medium size networks typical of social life (but also of some ecological, biological, neurological phenomena).

VNA preserves data ambiguity

As most statistical indicators, graph metrics discard much of the complexity of the empirical phenomena and focus on the few dimensions that can be precisely quantified (Desrosières, 1993). This *reduction to exactitude* can be a drawback in the exploratory stage of investigation, when the definition of the research questions is still underway and the mastery of the research corpus is still tentative. As long as the separation between "information" and "noise" (or "measure" and "error", if you prefer) remains unclear, efforts to *clean up the picture* risk to *cut* observation along precise but fallacious lines. In early stages, researchers should respect the inherent ambiguity of their subjects rather than imposing them a premature and artificial ordering. In Tukey's words:

> "Far better an approximate answer to the *right* question, which is often vague, than an *exact* answer to the wrong question, which can always be made precise." Data analysis must progress by approximate answers, at best, since its knowledge of what the problem really is will at best be approximate. It would be a mistake not to face up to this fact, for by denying it, we would deny ourselves the use of a great body of approximate knowledge (Tukey, 1962: 14, original emphasis).

Maintaining margins of ambiguity is particularly important in human and social sciences. Because of the complex nature of their objects, many researchers in these fields cannot bear the degree of exactitude implied by confirmatory statistics. If many human and social scientists are wary of quantitative tools, it is because their abstraction is at odds with the singularity, reflexivity and richness of human phenomena. Johanna Drucker (2011), for example, argues that standard charts convey a purity that is unrealistic for most social categories.

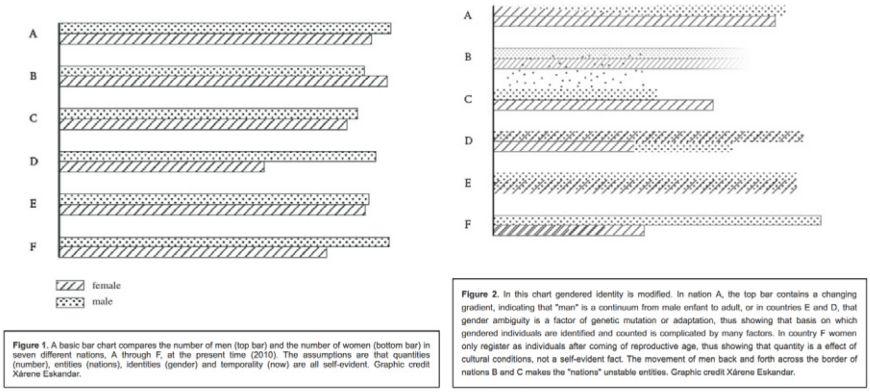

Figure 8 *A classic statistical chart (left) and its redesign with some of the original ambiguity (right) (original images and captions from Drucker, 2011)*

This is one of the reasons why network visualizations are increasingly popular as ways to explore complex subjects: their visual ambiguity mirrors some of the empirical ambiguity of the phenomena they represent. The community structure of networks is, for instance, notoriously ambiguous. As argued by Calatayud et al. (2019), for some empirical networks, the "solution landscape" of community detection "is degenerate" because "small changes in an algorithm parameter or a network due to noise can drastically change the best solution" (see also Peixoto, 2019 & 2020). In other words, for many networks, very different partitions are equally valid. In this situation, an ambiguous visualization may be more correct than a precise mathematical partitioning. Where community-detection algorithms tend to generate clear-cut and (generally) non-overlapping partitions, force-directed layouts reveal zones of different relational density but with blurred and uncertain borders. VNA is capable of preserving the inherent vagueness of concepts such as clusters, centres, fringes and bridges. Network metrics (and network models) are great tools to test for relational hypotheses, but network maps can be more appropriate when the problem is to explore uncertain phenomena. Not *despite* their ambiguity, but *because* of it. Because they are problematic, graph visualizations incite researchers to problematize their observations and encourage an enquiring attitude (Dewey, 1938).

4. Toward a measure of spatialization quality

Effective in practice, visual network analysis remains conceptually underdeveloped. As observed by Bernhard Rieder and Theo Röhle: "tools such as Gephi have made network analysis accessible to broad audiences that happily produce network diagrams without having acquired a robust understanding of the concepts and techniques the software mobilizes. This more often than not leads to a lack of awareness of the layers of mediation network analysis implies and thus to limited or essentialist readings of the produced outputs that miss its artificial, analytical character" (Rieder & Röhle, 2017).

In order to master VNA it is crucial to appreciate not only its strengths, but also its biases. Many of these biases come from the difficulty to separate in the visualization of networks the ‘positive ambiguity’ inherited from the represented phenomenon from the distortions coming from fitting a multidimensional mathematical object in the two dimensions of a computer screen (or piece of paper). The next figure illustrates the problem. While a chain of four nodes can be drawn in a way that is directly justifiable by its relational properties, a clique of four cannot – since all nodes are equally connected they should be at equal distance one from another, which is impossible (unless, of course, if all nodes are positioned in the exact same point). Force-driven layouts, like any other dimensionality reduction techniques, entail distortions and losses of information.

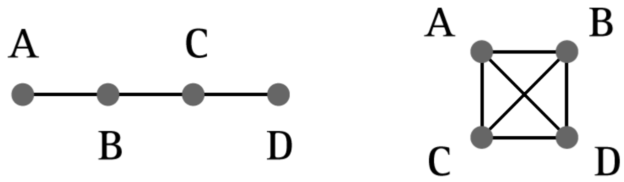

Figure 9 An exact network spatialization (left) – A necessarily skewed network spatialization (right)

Gauging embedding distortion, however, is far from easy, because of the difficulty to find a ground truth against which to evaluate the performance of force-directed layouts. We offer here two complementary perspectives on layout quality assessment: without and with assuming the existence of clusters. These two small experiments illustrate the difficulty of the endeavor. The first experiment follows the main argument of this paper, and assumes that the layout can manifest the community structure without requiring clear-cut cluster boundaries. Unfortunately, it poorly captures the heuristic qualities of known layouts. The second experiment uses a clear-cut community partition to assess layout quality, and it finds more consistent results. We subsequently reflect on the reasons why it is so difficult to assess quality as the visual translation of ambiguity, and we offer a direction for future research.

Experiment 1: assessing layout quality without assuming clusters

To assess how a layout respects the ambiguity of node relations, an obvious solution would be to compare the visual distance between them with their mathematical one. Unfortunately, not only several different mathematical distances exist in graph mathematics (making it difficult to choose one for comparison), but our results suggest that none of them captures the arrangement of force-directed spatialization.

In figure 10, we compare the Euclidean distance between each pair of nodes of the jazz network as spatialized by ForceAtlas2 (LinLog and gravity 0) with two classic mathematical distances: the l*ength of the shortest path* (geodesic distance) and the *mean commuting time*. This last quantity is defined as the average number of steps that a random walker, starting from one node, takes to reach the other and then go back to the starting node (Fouss et al., 2007). The Euclidean distance is somewhat correlated with the geodesic one, as expected, but the variability is very strong. There is almost no correlation with the mean commuting time, as random walkers can drift considerably far away from even a neighbouring node, especially when nodes’ degrees are high. Considering the distance between nodes discounts the topological nature of network spatializations, which, as explained in the previous section, aims at representing the underlying relational structures rather than at showing the connections between individual nodes.

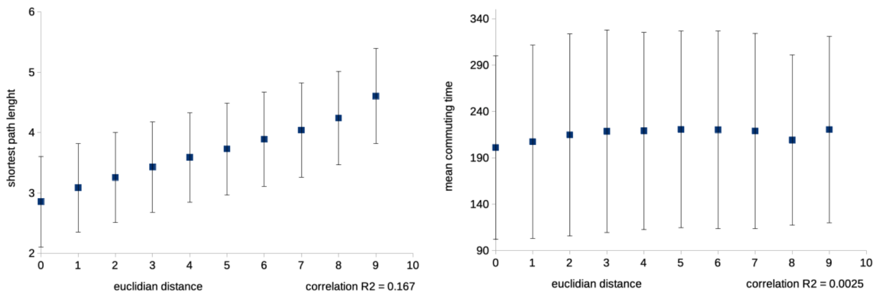

Figure 10 *scatter plots showing, for the jazz network, that the Euclidean distance in the spatialized network (ForsceAtlas2, LinLog mode, gravity = 0) is poorly correlated to both the shortest path and the random walk distances (respective R2 : 0.167 and 0.0025). The plot represents the mean and standard deviation as error bars) of the respective distances for the binned Euclidean distances "i" (i=int(distance / distance_max)).*

We assume here that the layout we used for the jazz network was as productive as it could be in practice, yet the correlation between visual and mathematical distances is poor for both distance metrics. This strategy does not capture the quality of the layout.

Experiment 2: assessing layout quality using a clustering

The correspondence between structural and visual clustering suggests a simple heuristic to gauge network layouts. Good layouts should suggest a visual partitioning roughly corresponding to its mathematical clustering. As an illustration, figure 11 shows the Jaccard similarity between the geometric cuts computed by k-means and the structural cuts computed by Louvain modularity (Blondel et al., 2008).

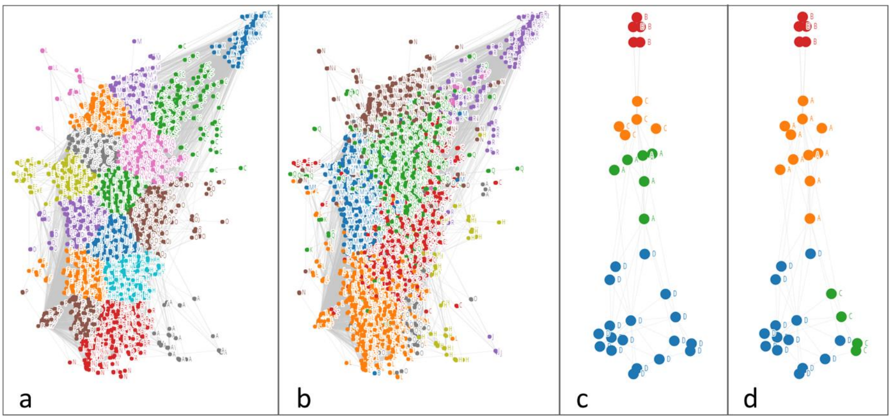

Figure 11 *Comparison of the clustering cuts identified by k-means (a and c) and Louvain modularity (b and d) on the jazz network and the karate club network.*

The bar chart presented in figure 12 confirms the insights of the images by proposing a more systematic comparison of the cuts identified by Louvain modularity and k-means (using the number of classes found by the Louvain algorithm in both cases) on three different networks (the jazz network, the karate club[6] and a clique) and four layouts (Force Atlas with gravity zero and linlog mode, default Force Atlas, default Früchterman & Reingold and a random layout). Each bar in the diagram represents the Jaccard similarity between the cuts of the two algorithms (Louvain modularity and k-means):

1. For a given network and a given partition of the nodes in *k* different classes *C*
2. We build the set *S* of all pairs of nodes (N_i, N_j) where the classes $C(N_i)$ and $C(N_j)$ are the same: $C(N_i) = C(N_j)$ (ie. the set of the node pairs that define the clusters).
3. To compare the two partitions *a* and *b* of the same network, we computer the Jaccard index of sets S_a and S_b as the number of common pairs (N_i, N_j), over the number of pairs are in either or both sets.

The Jaccard index has a value of 0 if the partitions have no node in common, and a value of 1 if they are exactly the same. Comparing the pairs of nodes has the benefit of not requiring matching each cluster of partition *a* with a cluster of partition *b*, which cannot always be done in a meaningful way (see the appendix for a more detailed comparison).

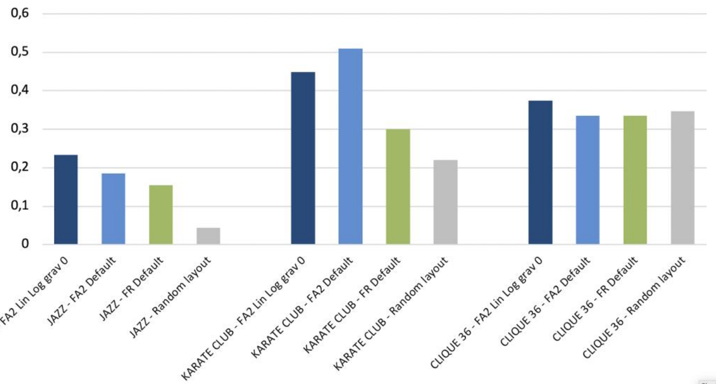

Figure 12 *Bar chart of the Jaccard similarity between the partitions identified by Louvain modularity and k-means on the jazz network, the karate club network and a clique of 36 nodes (higher is better).*

This simple comparison between modularity and k-means partitions works well on highly clustered networks, but not on networks that are more structurally ambiguous and that exhibit polarization rather than clustering (which is why the karate club network exhibits a higher cut similarity than the jazz network). This is not surprising. If, as we argued, the value of spatialization lies in its capacity to conserve and render ambiguity, such value will be poorly captured by a measure based on cuts.

This strategy is more successful than our first experiment (the community detection algorithm seems to better capture the structure than either topological distance used in experiment 1). However, as it takes for granted the existence of a clear-cut clustering, it fails to assess the ability of the layout to translate data ambiguity visually. In this case, retaining the best of both worlds would consist of assessing correspondence using an algorithm similar to community detection, but whose output would be a distance and not a partition. We have reasons to think that such a measure is attainable.

Can we find the node distances that best account for an ambiguous structure?

[6] The karate club is a famous network illustrating the alliances and opposition between the 34 members of a martial arts club as described by Wayne Zachary in a paper on "An Information Flow Model for Conflict and Fission in Small Groups" (1977).

As of today, we cannot offer a fully convincing answer to the problem of measuring the quality of force-directed spatialization; yet we can formulate the question as clearly as possible, framing the problem in a way that, hopefully, will help find a solution.

We start by reformulating the question of spatialization quality as follows: how close are force-directed algorithms to producing an optimal disposition of nodes? Interestingly, even though we have no precise definition of "optimal," we have two reasons to suspect that current algorithms may be near-optimal. The first is the pervasiveness of spatialization techniques. Not only have they been used for more than a decade with no major modifications, but they have also expanded to other areas. Indeed, dimensionality reduction algorithms in multivariate variable distribution, like t-SNE (van der Maaten & Hinton, 2008) and UMAP (McInnes et al., 2018), are implicitly building networks and spatializing them. The way they minimize entropy by gradient descent (GD) bears a striking resemblance to force-directed layouts. Both are iterative "relaxation" techniques converging to an approximate equilibrium and both are meant to optimize a function, which is explicit for GD and implicit for force-directed layouts (roughly corresponding to the energy of the system). The increasing success of T-SNE and UMAP suggests that the mathematical community has not found better than these quite similar techniques to produce interpretable visual objects.

The second reason is Andreas Noack's work on the LinLog algorithm. In his thesis, Noack (2007) proposes a layout quality metric called "normalized atedge length", corresponding to the total geometric length of the edges divided by the total geometric distance between all nodes and by the graph density. The smaller is the value of this metric, the more the layout has succeeded in representing relational communities as compact and separated visual clusters – for the numerator decreases when connected nodes are close (thus shortening the edges), and its denominator increases when disconnected nodes are far (thus increasing the overall distance).

Regrettably, the metric does not set an optimum expectation level and does not quantify the amount of bias due to the constraints of reducing dimensionality. It can, however, be used to compare different c and, as shown by Noack, to prove that the best results are produced by force-directed layouts employing a linear force of attraction (i.e. linearly proportional to the distance of nodes) and a logarithmic force of repulsion. Such is the principle of Noack's "LinLog" algorithm, often considered as the gold standard of spatialization quality.

In a later paper, Noack (2009) also demonstrated, for a very simple network, how the normalized atedge length is mathematically equivalent to modularity, a clustering quality metric used for community detection (Newman, 2006). This result provides evidence that the LinLog algorithm may be close to the optimum in the task of translating mathematical communities into a visual clustering. It also indicates that the problem of "normalized atedge length" minimization is probably NP-complete, as is the problem of maximizing modularity (Brandes et al., 2006). This indicates that it may be hard to outperform the iterative convergence of force-directed layouts by using a deterministic approach.

Searching for a spatialization quality metric is a case of "experimenter's regress" (Collins, 1975), a situation where we face a dependency loop between theory and empirical evidence. To avoid the confirmation bias, it is crucial to remember that the LinLog is an *empirical* gold standard, which still needs theoretical confirmation. We are not sure that Noack's "normalized atedge length" is the metric that should be minimized, and we have no proof that the LinLog is the best approach to minimize it. All we know is that the "normalized atedge length" is a reasonable definition of spatialization quality and that, among the existing layouts, LinLog is the one that delivers the best results according to it (while also being the one that makes clusters most visually salient).

Elements of a spatialization quality metric

To provide a solid mathematical ground for visual network analysis, however, we still need a spatialization quality metric independent from the current state of algorithms and based on a deeper theoretical ground. Such a metric would clarify the operation performed by force-driven placement algorithms and allow evaluating them. It should also have the following four features:

1. **A measure of spatialization quality should give a score to a network layout.** The metric must measure the quality an assignment of (x,y) coordinates for the nodes of a given network spatialized with a given algorithm.
2. **We expect existing force-directed layouts to perform well according to this metric.** Since our empirical ground truth (the only currently available) is the interpretability and usefulness of algorithms such as LinLog, we hypothesize that these algorithms accomplish a performance that the metric would capture and make explicit.
3. **The metric should be declined at the level of nodes and edges.** Beside evaluating the overall spatialization, we also hope the metric will indicate which nodes and edges are most biased.
4. **It should be interpretable.** We are aware that this is a difficult goal, but the metric should tell us *what a good spatialization is*. For instance, it might be that a good visualization is when edges are as short as possible, or that proximity relates to the length of the shortest path, or to structural equivalence. Unfortunately, as we have shown, all those explanations are wrong, so the measure should also figure out which other information is conveyed by the spatialization of networks.

Conclusion

This paper starts from the empirical observation that scholars in a variety of disciplines in social and natural sciences are increasingly employing network visualizations both as a preliminary way to gauge the structure of their relational datasets and as a way to convey an overview of their findings. The growing popularity of this type of charts suggests that, far from being merely decorative, points-and-lines visualizations have a distinctive heuristic force. Their use constitutes a form of network analysis, though one that is markedly different from that of the statistical metrics and models typically used in social network analysis and network science. This type of analysis, however, has so far remained a sort of "trick of the trade", whose virtues (but also whose limits) are seldom acknowledged or explicitly discussed. This lack of documentation explains the mistrust that many scholars still maintain against network visualization who is often (and not entirely unfairly) accused of generating sketchy and ill-defined findings.

In this paper we investigated this *evocative* power of network visualizations and we tried to explicitly reconstruct the method behind the tacit practices of visual network analysis. We did so by retracing the history of force-directed layouts and discussing the way in which they produce a space in which the mathematical structures of the graph can be read visually. While balancing the attraction forces of nodes and the repulsion forces of edges, force-directed algorithms generate a two-dimensional representation of networks in which clusters *tend to* appear as denser gatherings of nodes; structural holes *tend to* look like sparser zones; central nodes move *towards* middle positions; and bridges are positioned *somewhat* between different regions. We call this type of visualization *topological*, as its objective is to turn topological structures into visual patterns.

The value of this topological visualization, we argued, has been disregarded in the fields of both network visualization and of network analysis. On the one hand, in network visualization, force-directed layouts have been underestimated because their results have been judged from a diagrammatic perspective in which charts are used to identify paths between nodes (a task that is impossible even in medium-sized networks) rather than to grasp more general relational patterns. On the other hand, in network analysis, VNA has been discounted because of its inherent ambiguity and the impossibility to define with precision the meaning of proximity in a spatialized network. In this paper, we argued that this elusiveness is not a good reason to dismiss points-and-lines charts. Instead the ambiguity of points-and-lines charts should be tamed by separating the distortions coming from the projection of a multidimensional object in a two-dimensional space, from the blurriness inherent to relational phenomena that should not be evacuated, but rather cherished and investigated.

Distinguishing a good ambiguity from a bad one, however, is not an easy task and in the last section we discussed a few mathematical reasons why this is the case. Waiting for a precise measure of spatialization quality, however, VNA can still be productively used as a tool for exploratory data analysis. In this paper we described and exemplified a series of techniques that we developed to this objective, hoping to help researchers to be more mindful in the use of network charts and build trust and understanding around a form of analysis that is widely used, but so far insufficiently investigated.

References

Aris, Aleks, and Ben Shneiderman. 2007. "Designing Semantic Substrates for Visual Network Exploration." *Information Visualization* 6(4): 281–300.

Bastian, Mathieu, Sebastien Heymann, and M. Jacomy. 2009. "Gephi: An Open Source Software for Exploring and Manipulating Networks." In *International AAAI Conference on Weblogs and Social Media*, , 361–62. http://www.aaai.org/ocs/index.php/ICWSM/09/paper/download/154/1009 (December 16, 2010).

Behrens, John T, and Yu Chong-Ho. 2003. "Exploratory Data Analysis." In *Handbook of Psychology*, ed. Irving B. Weiner. London: Wiley, 33–64. https://scholar.google.com/scholar?hl=en&q=Exploratory+Data+Analysis+++hartwig&btnG=&as_sdt=1,5&as_sdtp=.

Bertin, Jacques. 1967. *Sémiologie Graphique*. Paris - La Haye: Mouton.

Blondel, Vincent D., Jean-Loup Guillaume, Renaud Lambiotte, and Etienne Lefebvre. 2008. "Fast Unfolding of Communities in Large Networks." *arxiv.org*: 1–12. http://arxiv.org/abs/0803.0476%0Ahttp://dx.doi.org/10.1088/1742-5468/2008/10/P10008.

Boullier, Dominique, Maxime Crépel, and Mathieu Jacomy. 2016. "Zoomer n'est Pas Explorer." *Réseaux* 195(1): 131–61.

Brandes, U. et al. 2006. "Maximizing Modularity Is Hard." (001907). http://arxiv.org/abs/physics/0608255.

Brandes, U., P. Kenis, and J. Raab. 2006. "Explanation through Network Visualization." *Methodology* 2(1): 16–23.

Brandes, U., and D. Wagner. 2004. "Analysis and Visualization of Social Networks." In *Graph Drawing Software*, Berlin Heidelberg: Springer, 321–40.

Burt, Ronald S. 1995. *Structural Holes: The Social Structure of Competition*. Cambridge Mass: Harvard University Press. http://books.google.com/books?id=E6v0cVy8hVIC&pgis=1 (May 16, 2012).

Calatayud, J., Bernardo-Madrid, R., Neuman, M., Rojas, A. and Rosvall, M., 2019. Exploring the solution landscape enables more reliable network community detection. *Physical Review E*, 100(5), p.052308.

Collins, H M. 1975. "The Seven Sexes: A Study in the Sociology of a Phenomenon, or the Replication of Experiments in Physics." *Sociology* 9: 205–24. http://soc.sagepub.com/content/9/2/205.abstract.

Correa, C.D., and K.L. Ma. 2011. "Visualizing Social Networks." In *Social Network Data Analytics*, Boston: Springer, 307–26.

de Nooy, Wouter. 2003. "Fields and Networks: Correspondence Analysis and Social Network Analysis in the Framework of Field Theory." *Poetics* 31(5–6): 305–27. http://linkinghub.elsevier.com/retrieve/pii/S0304422X03000354 (July 27, 2011).

Decuypere, Mathias. 2020. Visual Network Analysis: a qualitative method for researching sociomaterial practice. *Qualitative Research*, 20(1), 73-90.

Desrosières, Alain. 1993. *La Politique Des Grands Nombres : Histoire de La Raison Statistique*. Paris: La Découverte. http://www.amazon.fr/politique-grands-nombres-Histoire-statistique/dp/2707165042 (September 26, 2011).

Dewey, John. 1938. *Logic: The Theory of Inquiry*. New York: Holt, Rinehart And Winston.

Di Battista, Giuseppe, Peter Eades, Roberto Tamassia, and Ioannis G. Tollis. 1999. *Graph Drawing: Algorithms for the Visualization of Graphs*. Upper Saddle River: Prentice Hall.

Drucker, Johanna. 2011. “Humanities Approaches to Graphical Display.” *DHQ: Digital Humanities Quarterly* 5(1): 1–20.

Dunne, Cody, and Ben Shneiderman. 2009. “Improving Graph Drawing Readability by Incorporating Readability Metrics: A Software Tool for Network Analysts.” *HCIL Tech Reports (HCIL-2009-13)* (April): 1–9.

Fouss, Francois, Alain Pirotte, Jean-michel Renders, and Marco Saerens. 2007. “Random-Walk Computation of Similarities between Nodes of a Graph with Application to Collaborative Recommendation.” *IEEE Transactions on Knowledge and Data Engineering* 19(3): 335–69.

Freeman, Linton C. 2000. “Visualizing Social Networks.” *Journal of Social Structure* 1(1).

Freeman, Linton C. 2009. “Methods of Social Network Visualization.” In *Encyclopedia of Complexity and Systems Science*, ed. R. A. Myers. Berlin: Springer, 1–17.

Fruchterman, Thomas MJ, and Edward M Reingold. 1991. “Graph Drawing by Force-directed Placement.” *Software: Practice and Experience* 21(NOVEMBER): 1129–64. http://onlinelibrary.wiley.com/doi/10.1002/spe.4380211102/abstract (September 23, 2014).

Gibson, Helen, Joe Faith, and Paul Vickers. 2013. “A Survey of Two-Dimensional Graph Layout Techniques for Information Visualization.” *Information Visualization* 12(3–4): 324–57.

Gleiser, Pablo, and Leon Danon. 2003. “Community Structure in Jazz.” *Advances in Complex Systems* 6(4): 565–73. http://arxiv.org/abs/cond-mat/0307434%0Ahttp://dx.doi.org/10.1142/S0219525903001067.

Grandjean, Martin, and Jacomy, Mathieu. 2019. Translating Networks: Assessing Correspondence Between Network Visualisation and Analytics. *Digital Humanities 2019*.

Hadlaw, Janin. 2003. “The London Underground Map: Imagining Modern Time and Space.” *Design Issues* 19(1): 25–35. http://www.mitpressjournals.org/doi/10.1162/074793603762667674.

Hansen, D.L. et al. 2012. “Do You Know the Way to SNA?: A Process Model for Analyzing and Visualizing Social Media Network Data.” In *International Conference on Social Informatics*, IEEE, 304–13.

Henry, Nathalie, Jean-daniel Fekete, and Michael Mcguffin. 2012. “NodeTrix : A Hybrid Visualization of Social Networks To Cite This Version : NodeTrix : A Hybrid Visualization of Social Networks.” *IEEE Transactions on Visualization and Computer Graphics*.

Jacomy, Mathieu, Paul Girard, Benjamin Ooghe, and Tommaso Venturini. 2016. “Hyphe, a Curation-Oriented Approach to Web Crawling for the Social Sciences.” In *International AAAI Conference on Web and Social Media*, , 595–98. https://hal.archives-ouvertes.fr/hal-01293078/.

Jacomy, Mathieu, Tommaso Venturini, Sebastien Heymann, and Mathieu Bastian. 2014. “ForceAtlas2, a Continuous Graph Layout Algorithm for Handy Network Visualization Designed for the Gephi Software.” *PloS one* 9(6): e98679. http://www.ncbi.nlm.nih.gov/pubmed/24914678 (June 17, 2014).

Jokubauskaite, Emilija. 2018. *Gephi and its Context: Three Oppositions in The Epistemic Culture of Network Analysis And Visualisation*. University of Amsterdam.

Lima, Manuel. 2014. *The Book of Trees: Visualizing Branches of Knowledge*. New York: Princeton Architectural Press.

McAndrew, Siobhan, Paul Widdop, and Rachel Stevenson. 2014. “On Jazz Worlds.” In *Social Networks & Music Worlds*, eds. Nick Crossley, Siobhan McAndrew, and Paul Widdop. London.

McInnes, Leland, John Healy, and James Melville. 2018. “UMAP: Uniform Manifold Approximation and Projection for Dimension Reduction.” *arXiv*. http://arxiv.org/abs/1802.03426.

Moreno, Jacob. 1953. *Who Shall Survive? (Second Edition)*. New York: Beacon House Inc.

Newman, M E J. 2006. “Modularity and Community Structure in Networks.” *Proceedings of the National Academy of Sciences of the United States of America* 103(23): 8577–82. http://www.pubmedcentral.nih.gov/articlerender.fcgi?artid=1482622&tool=pmcentrez&rendertype=abstract (July 16, 2014).

Nick, B., C. Lee, P. Cunningham, and U. Brandes. 2013. “Simmelian Backbones: Amplifying Hidden Homophily in Facebook Networks.” In *Proceedings of the 2013 IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining*, ACM Press, 525–32.

Noack, Andreas. 2007. “An Energy Model for Visual Graph Clustering” ed. Giuseppe Liotta. *Journal of Graph Algorithms and Applications JGAA* 11(112): 453–80. http://link.springer.com/chapter/10.1007/978-3-540-24595-7_40 (September 23, 2014).

Noack, Andreas. 2007. “Unified Quality Measures for Clusterings, Layouts, and Orderings of Graphs, and Their Application as Software Design Criteria.”

Noack, Andreas. 2009. “Modularity Clustering Is Force-Directed Layout.” *Physical Review E* 79(2). http://link.aps.org/doi/10.1103/PhysRevE.79.026102 (July 11, 2011).

Ooghe-tabanou, Benjamin, Paul Girard, and Guillaume Plique. 2018. “Hyperlink Is Not Dead !” In *Digital Tools & Uses Congress*, Paris: ACM Press.

Peixoto, Tiago P., 2019. Bayesian stochastic blockmodeling. in Patrick Doreian, Vladimir Batagelj, Anuška Ferligoj (eds.) *Advances in network clustering and blockmodeling*, pp. 289-332.

Peixoto, Tiago P., 2020. Revealing consensus and dissensus between network partitions. *arXiv preprint* arXiv:2005.13977.

Purchase, Helen C., Robert F. Cohen, and Murray James. 1996. “Validating Graph Drawing Aesthetics.” In , 435–46. http://link.springer.com/10.1007/BFb0021827.

Purchase, Helene C. 2002. “Metrics for Graph Drawing Aesthetics.” *Journal of Visual Languages & Computing* 13: 501–16. http://www.sciencedirect.com/science/article/pii/S1045926X02902326 (November 19, 2014).

Rieder, Bernhard, and Theo Röhle. 2017. “Digital Methods From Challenges to Bildung.” In *Datafied Society*, eds. Mirko Tobias Schäfer and Karin van Es. Amsterdam: University Press, 109–24.

Scott, John. 1991. *Social Network Analysis*. Thousand Oaks California: Sage.

Shneiderman, Ben, and Cody Dunne. 2013. “Interactive Network Exploration to Derive Insights: Filtering, Clustering, Grouping, and Simplification.” In *International Symposium on Graph Drawing 2012*, , 2–18. http://link.springer.com/10.1007/978-3-642-36763-2_2.

Soni, U. et al. 2018. “The Perception of Graph Properties in Graph Layouts.” *Computer Graphics Forum* 37(3): 169–81.

Sonnett, John. 2016. “Ambivalence, Indifference, Distinction: A Comparative Netfield Analysis of Implicit Musical Boundaries.” *Poetics* 54: 38–53. http://dx.doi.org/10.1016/j.poetic.2015.09.002.

ter Braak, Cajo J. F. 1986. “Canonical Correspondence Analysis: A New Eigenvector Technique for Multivariate Direct Gradient Analysis.” *Ecology* 67(5): 1167–79. http://doi.wiley.com/10.2307/1938672.

The New York Times. 1933. “Emotions Mapped by New Geography.” *The New York Times* 3 April.

Tukey, J. 1977. *Exploratory Data Analysis*. Reading, Massachusetts: Addison-Wesley.

Tukey, John Wilder. 1962. “The Future of Data Analysis.” *The Annals of Mathematical Statistics* 33(1): 1–67.

Turnbull, David. 2000. *Masons, Tricksters and Cartographers*. London: Routledge.

van der Maaten, Laurens, and Geoffrey Hinton. 2008. “Visualizing Data Using T-SNE.” *Journal of Machine Learning Research* 9: 2579–2605.

Vlegels, Jef, and John Lievens. 2017. “Music Classification, Genres, and Taste Patterns: A Ground-up Network Analysis on the Clustering of Artist Preferences.” *Poetics* 60: 76–89. http://dx.doi.org/10.1016/j.poetic.2016.08.004.

Wasserman, Stanley, and Katherine Faust. 1994. *Social Network Analysis: Methods and Applications: Methods and Applications*. Cambridge: University Press. http://books.google.com/books?hl=en&lr=&id=CAm2DpIqRUIC&oi=fnd&pg=PR21&dq=scott+and+carrington+social+network+methods&ots=HuLuze3BNi&sig=dRJDJvtPH2eSS1VKZoWZn92r1v0%5Cnpapers2://publication/uuid/EB17CF58-99C3-4B1B-BE59-608AC77615C5.

Yan, Shuicheng et al. 2007. “Graph Embedding and Extensions: A General Framework for Dimensionality Reduction.” *IEEE Transactions on Pattern Analysis and Machine Intelligence*.

Zachary, Wayne W. 1977. “An Information Flow Model for Conflict and Fission in Small Groups.” *Journal of Anthropological Research* 33(4): 452–73. http://www.journals.uchicago.edu/doi/10.1086/jar.33.4.3629752.

APPENDIX E. ACTOR-NETWORK VS. NETWORK ANALYSIS VS. DIGITAL NETWORKS

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Actor-Network versus Network Analysis versus Digital Networks

Are We Talking about the Same Networks?

Tommaso Venturini, Anders Kristian Munk, and Mathieu Jacomy

Odi et amo. quare id faciam, fortasse requiris?
nescio, sed fieri sentio et excrucior.
Catullus 85 or Carmina LXXXV

Professor: You should not confuse the network that is drawn by the description and the network that is used to make the description.

Student: . . . ?

Professor: But yes! Surely you'd agree that drawing with a pencil is not the same thing as drawing the shape of a pencil. It's the same with this ambiguous word, network. With actor-network you may describe something that doesn't at all look like a network—an individual state of mind, a piece of machinery, a fictional character; conversely, you may describe a network—subways, sewages, telephones—which is not all drawn in an "actor-networky" way. You are simply confusing the object with the method. ANT is a method, and mostly a negative one at that; it says nothing about the shape of what is being described with it.

Student: This is confusing! But my company executives, are they not forming a nice, revealing, significant network?

Professor: Maybe yes, I mean, surely, yes—but so what?

Student: Then, I can study them with actor-network theory!

Professor: Again, maybe yes, but maybe not. It depends entirely on what you yourself allow your actors, or rather your actants to do. Being connected, being interconnected, being heterogeneous, is not enough. It all depends on the sort of action that is flowing from one to the other, hence the words "net" and "work." Really, we should say "worknet" instead of "network." It's the work, and the movement, and the flow, and the changes that should be stressed. But now we are stuck with "network" and everyone thinks we mean the World Wide Web or something like that.

Student: Do you mean to say that once I have shown that my actors are related in the shape of a network, I have not yet done an ANT study?
Professor: That's exactly what I mean: ANT is more like the name of a pencil or a brush than the name of an object to be drawn or painted.

—Bruno Latour, 2005, *Reassembling the Social: An Introduction to Actor-Network Theory,* Oxford: Oxford University Press (pp. 142, 143)

From Conflation Comes Power

Say what you want, analytical dissection is not the only motive of science. Often, the desire to fit together concepts coming from different traditions and disciplines feels just as urgent. A good example is the conflation that in the last three decades has seen three different meanings of the word "network" merge in STS.

It arguably began in 1986 when Michel Callon introduced the term "actor-network" as a conceptual tool to "describe the dynamics and internal structure of actor-worlds" (Callon 1986, 28). It is worth remembering that Callon's essay appeared in the volume *Mapping the Dynamics of Science and Technology*, a book that intended to complement the traditional ethnographic techniques employed in STS with new methods derived from scientometrics and text analysis.

Three ingredients of network conflation were already there:

1. The theoretical idea that collective phenomena are best described not by the substances, but by the relations that constitute them (actor-network theory)
2. The methodological appeal for new quantitative techniques to analyze and represent the connections between social actors (network analysis)
3. The intuition that the inscriptions left by collective actions (scientific publication in the specific case) could be repurposed for social research (network data)

The ambiguity of the word "network"—which can equally refer to a conceptual topology (the space of connections as opposed to the Euclidian space of coordinates), to a set of computation techniques (the mathematics of graphs), and to the hypertextual organization of inscriptions (the relational datasets)—suggested that the conflation was possible and, indeed, desirable.

Conflating these otherwise disparate notions of "network" was more than a conceptual trick. It involved wedding the ideas of actor-network theory (ANT) to some of the methods of social network analysis (SNA). The marriage was particularly appealing because it promised a way to follow sociotechnical associations across sites (see Knorr Cetina 1995; Vinck 2012). But the wedding had appeal to social network analysts as well, who could find in it the theoretical framework that they had missed (Granovetter 1979 laments a "Theory-Gap in Social Network Analysis" and Burt 1980 argues that "the lack of network theory seems to me to be the most serious impediment to the realization of the potential value of network models in empirical research"; 134).

Yet, for quite some time, the marriage between ANT and SNA bred few progeny. ANT scholars felt the appeal of SNA techniques, but were afraid their definition of "social relations" would be too narrow. Having spent half a decade defending the role of nonhuman actors, actor-network theorists could not settle for networks restricted to human beings.

Hence the interest for scientific inscriptions and more generally for the variety of "intermediary objects" (scientific papers, technological devices, animal models, measuring instruments) producing relational data complementary to that of human relations. Many of such objects exhibited connections that could be traced and analyzed (Vinck 2012). Studying them produced the first embryo of the hybrid addressed in this article: a quali-quantitative approach to heterogeneous networks (Venturini and Guido 2012). The qualitative observations realized in science and technology studies suggested new applications for the quantitative techniques of network analysis. Callon, for example, started investigating co-occurrence in titles after observing (through ethnographic work) that the association of words was commonly used as an "interestment device."

Still, collecting traces on such hybrid networks was as demanding as traditional ethnographic work (if not more), and the shortage of relational data limited the interest of the ANT/SNA conflation. Such shortage was overcome with the advent of yet another type of networks, namely those emerging from digital mediation. Speaking at the Virtual Society? conference (Woolgar 2002), Bruno Latour (1998) suggested that social connections become more material and thereby more traceable when flowing through digital infrastructures: "Once you can get information as bores, bytes, modem, sockets, cables and so on, you have actually a more material way of looking at what happens in Society. Virtual Society thus, is not a thing of the future, it's the materialisation, the traceability of Society. It renders visible because of the obsessive necessity of materialising information into cables, into data." In the audience were two young sociologists, Richard Rogers and Noortje Marres, who, in the following years, developed a series of tools and methods to put digital traces at the service of the social sciences (see Rogers 2004, 2013; Rogers and Marres 2000, 2002; www.digitalmethods.net): "Bruno Latour (1998), argued that the Web is mainly of importance to social science insofar as it makes possible new types of descriptions of social life. According to Latour, the social integration of the Web constitutes an event for social science because the social link becomes traceable in this medium. Thus, social relations are established in a tangible form as a material network connection. We take Latour's claim of the tangibility of the social as a point of departure in our search" (Rogers and Marres 2002, 342). It is important to notice that it is not the volume of digital data that made the difference (this is *not* a "big data" argument), but its relational nature. As digital media are organized as networks at the both physical and content levels (the Internet is the interconnection of computer networks and the World Wide Web is the interconnection of online hypertexts), the inscriptions that they produce are *natively* relational. TPC/IP (Transmission Control Protocol / Internet Protocol), HTTP (Hypertext Transfer Protocol), the Relational Databases, and all major protocols and formats supporting digital communication are relations based.

By generalizing the practice of citation beyond the scientific literature (Leydesdorff 1998; Leydesdorff and Wouters 1999), digital protocols contributed to formalize collective life as a network of association, both in the sense of extending the reach of the network methods developed in scientometrics (see, for example, how Roth and Cointet 2010 employed the exact same techniques to study scientists working on the zebra fish and US political bloggers) and in the sense of encouraging collective life to organize in network-like shapes: "We took to the Web to study public debates on science and technology, but we found 'issue-networks' instead. . . . Following hyperlinks among pages dealing with a given issue, we found that these links provided a means to demarcate the network that could be said to be staging the controversy in the new medium" (Marres and Rogers 2005, 922). It would be nice here to tell the story of social sciences revealing the nature of a new medium and repurposing its formats for research. Things, however, are more complex, and while social scientists were striving to socialize web networks, computer scientists were busy engineering sociological methods—and scientometrics in particular—into digital media (Marres 2012a). The most famous example is contained in the article presenting PageRank, the algorithm that made the success of Google, where its inventors explicitly argue, "It is obvious to try to apply standard citation analysis techniques to the hypertextual citation structure of the web. One can simply think of every link as being like an academic citation" (Page et al. 1998, 2). This explains why the network conflation is so powerful: it is not just the meeting of two separate sociological schools; it is that this meeting takes place on the ground of one of the major technological (and economic) innovations of the last century. If it feels more and more natural to think of collective phenomena in relational terms, it is because digital mediation is increasingly turning them into networks. Our professional sector much more resembles a social network since our colleagues invited us on LinkedIn. Friendship has literally become a matter of connection, now that it is mediated by Facebook. And when we look at our library, we increasingly expect to see what other books "Customers Who Bought This Item Also Bought." The more it is mediated by network technologies, the more collective life can be read through the theory of networks, measured through network analysis, and captured in network data. "Sociologists of technology have long relied on methods of network and textual analysis in order to capture the unfolding of controversies. . . . Today the proliferation of digital technologies means that similar methods are deployed much more widely to analyse and visualise issues in digital networked media. . . . Indeed, network and textual analysis tools are now routinely deployed in digital culture" (Marres 2012a, 300). The (con)fusion of the four meanings of "network" (a conceptual metaphor, an analytic technique, a set of data, a sociotechnical system) is not just a product of sociology; it is a product of society. This is why the network conflation is so powerful—to the point that great is the temptation to argue not only that collective phenomena can be described and mediated through networks but also that society has in fact become a network (see Castells 2000; Van Dijk 1999) and even that everything has become a network (see Barabási 2002). And this is why the network conflation is so dangerous.

Networks Are Not Networks

As the uncle of Spiderman used to say, "With great power comes great responsibility," and the very same people who initiated the network conflation in STS, the actor-network theorists, have always been wary about its use and abuse. In particular, they were afraid that, while offering an operationalization of their relational analysis, it also risked blurring important parts of their approach. They were right.

The easiest way to answer the question asked by this chapter—"are we talking about the same networks?"—is with a simple "no, we are not." The networks captured by digital data and analyzed through the canon of graph mathematics do not resemble actor-networks in at least *four* respects.

Partiality and Bias of Digital Inscriptions

The first concerns the relational data that, as we said, catalyzed the fusion between ANT and network analysis. It is obvious but deserves to be mentioned: digital traces (like any other type of inscription) are not always representative of the phenomena that they allow to trace.

There are two main reasons for this. First, not all relevant collective actions are mediated by digital infrastructures: despite the growing extent to which digital mediation has infiltrated social life, there are still important interactions that fall beyond them. For instance, despite the advances in digitalization, the production of science and technology still relies on face-to-face interaction and direct manipulation. All the online journals and libraries will not replace the discussions in the corridors of conferences and all the computer simulations are no substitute for in vivo measure and in vitro experiments.

Second, digital technologies (as all media) do not just trace, but also translate the interactions that they support. Digital media are not the carbon paper that trace our writing, they are the paper that replace the parchment, thereby substantially affecting the nature of the books we write and read (Eisenstein 1980). This is not an abstract argument: working with digital traces entails a constant questioning of the findings obtained: What do I see when I examine the evolution of a hashtag? Public opinion, or Twitter (Marres and Gerlitz, 2015)? Digital inscriptions are not created by or for the social sciences; they are the product of vast sociotechnical systems comprising online platforms, commercial start-ups, communication protocols, fiber cables, and so forth, and bring with them the influences of such system. This is not to say, to be sure, that digital traces are more biased than other types of inscriptions, but that the conditions of their production are always to be remembered (Munk 2013; Venturini et al. 2014).

This first hitch concerns the catalyst (digital traces) that made possible the reaction between ANT and SNA, but other difficulties emerge when actor-networks and mathematical networks are compared. We describe them in the next paragraphs with reference to *conventional* graph mathematics. By *conventional*, we refer to the methods and tools that are implemented in standard network analysis. Though extensions have been proposed to overcome many of the limitations of conventional network analysis (see, for instance, Everett and Borgatti 2014 on negative connections and Chavalarias and Cointet 2013 on dynamic clustering), their experimental character has prevented them (so far at least) from entering the toolkit of social research.

Heterogeneity of Nodes and Edges

The first difference between graph mathematics and actor-networks was pointed out by Michel Callon (1986) in the very article in which he introduced the notion of the actor-network: "[An actor-network] is distinguished from a simple network because its elements are both heterogeneous and are mutually defined in the course of their association" (32). One of the ideas that aroused most interest around ANT is its extremely broad definition of social actors. According to ANT, social phenomena involve not only individuals (e.g., scientists and engineers) but also collective assemblages (e.g., laboratories and academic institutions), nonhuman actors (e.g., natural substances and technical devices), and even conceptual items (e.g., scientific theories and legal frameworks). At a first glance, this openness matches well with the agnosticism of graphs, whose elements have been used to represent almost everything (from websites to neurons, from proteins to words). Yet while actor-networks allow and even prescribe the presence of items of different nature in the same network, graph nodes tend to be of the same type.

The reason is simple: graph mathematics is hardly capable of handling qualitative differences. The items in a graph can be quantitatively different (as they may carry different "weights"), but they are all mathematically equivalent. It is possible to build networks with nodes of different type (see, for instance, Cambrosio et al. 2004), but belonging to one type or another will not affect what nodes can or cannot do.

This limitation is felt more strongly for edges than for nodes and sometimes referred to as the problem of "parallel edges." Imagine a network of Facebook accounts. As long as edges are limited to one type of connection (say friendship links), graph analysis can deliver interesting results (see Rieder 2013). But as soon as we try to project different types of relations *on the same network*, we stumble on the problem of weighting: How many "likes" should count as a comment? How much weaker does a friendship get when it is "unfollowed" (removed from the user's news feed)? Is posting a text stronger or weaker than posting an image? And, of course, combining traces coming from different platforms and media compounds the problem.

Negative relations are especially complicated. Collective life is made of opposition as much as of alliances, but conventional graph mathematics offers no convincing way to handle "negatively charged" edges. In network analysis, opposition is generally operationalized as a lack of association (see the concept of "structural hole" by Burt 1995). In citation analysis, for instance, it is commonly accepted that "there is no such thing as negative publicity." Garfield, one of the fathers of scientometrics, makes it very clear: "If scientists tend to ignore inferior work that is of little importance, then the work that they do go to the trouble of formally criticizing must be of some substance. Why, then, should negative citations be considered a sign of discredit?" (1979, 361–62).

This work-around has been successfully used to exploit network analysis for controversy mapping (Venturini 2010, 2012) and produced interesting results when applied to digital data (see, for instance, Adamic and Glance 2005). It often happens, however, that digital traces provide us information directly about opposition. For instance, studying controversies in Wikipedia, we can easily access "reverts" and other antagonistic edits, but to exploit them to detect "edit-factions" we need to turn the network around, according to the principle of "my enemy's enemy is my friend" (Borra et al. 2014).

Reversibility of Actor-Network

The second glitch in network conflation has to do with the hyphen connecting actor and network in ANT. This little typographical character is of critical importance and often misunderstood. The wrong way to read the hyphen is as a pointer to the interactions between the social actors and the system that would contain them: "the idea was never to occupy a position into the agency/structure debate, not even to overcome this contradiction. Contradictions should not be overcome, but ignored or bypassed" (Latour 1999, 15). Rather, the hyphen stands for an equal: actor=network: "To try to follow an actor-network is a bit like defining a wave-corpuscle in the 1930s: any entity can be seized either as an actor (a corpuscle) or as a network (a wave). It is in this complete reversibility—an actor is nothing but a network, except that a network is nothing but actors—that resides the main originality of this theory" (Latour 2010, 5). The hyphen is not meant to connect the two halves of the expression (actor *and* network), it is meant to deny *both* (*neither* actor *nor* network). Paradoxical as it may sound, in the world of actor-network there are no actors (entities defined by properties independent from the relations connects them) and no networks (structures defined by patterns independent from the elements that they connect).

This reversibility is absent from graph mathematics, where nodes and networks are described by different properties and measured by different metrics. It is even commonly accepted that SNA techniques can be separated in two analytic toolkits: one to study the ego networks (centered on a single node and its neighbors; see White 2000) and another to study global networks. Though such a distinction is more apparent than real (the two toolkits are based on the same graph mathematics), there is indeed a substantial difference in the way SNA conceives nodes (indivisible and impenetrable items) and networks (global and composite structures). And this difference aligns closely with the classic divides of social theory (micro/macro, interactions/structures, individuals/institutions, local/global, etc.; see Giddens 1984; Archer 1995) that ANT has always rejected (Callon and Latour 1981).

However, when looking at the actual techniques of network analysis, the separation between nodes and networks appears less significant. All the key properties of nodes (authority, centrality, betweenness, etc.) depend on the overall topology of the network in which they are located and, conversely, all the key properties of networks (diameter, modularity, clustering, etc.) depend on the local arrangements between nodes. In graph mathematics, nothing can be calculated about networks without considering each node and little can be calculated about nodes without considering the network it its entirety.

This is particularly more visible in the digital implementations of social networks (Latour et al. 2012). Consider, for instance, how Facebook breached earlier WWW conventions by developing a website without a homepage and without individual pages. And Facebook is no exception. All the homepages of the main Web2.0 platforms (Twitter, Flickr, Tumblr, Pinterest, etc.) are remarkably empty and systematically deserted by their users (how many times have you visited the homepage of Wikipedia?). But what is most striking about Facebook is that even the individual pages are of little importance. Yes, users can choose their name, edit their description, and upload a cover photo, but what core of their account is the "wall" in which the users' posts are mixed with (often drown in) the contents published by their "friends." The largest online social network is not a global structure lodging an ensemble of individuals (actors *and* network). It is a constant flux of recombinable contents relentlessly clotting and dissolving (actor=network) (see a similar analysis of Flickr by Boullier and Crépel 2012).

Dynamics of Relational Change

The last and possibly the most serious divergence between ANT and network analysis concerns time. ANT is essentially a theory of change. Its focus is not on the structure of associations, but on their dynamics. “Reality,” writes Michel Callon, “is a process. Like a chemical body, it passes through successive states” (Callon 1984, 207). The difficulty in accounting for time as networks is not only a problem for ANT. According to Mustafa Emirbayer (1997), time remains one of the main obstacles in the operationalizing all relational sociologies: “Paradoxically (for a mode of study so intently focused upon processuality), relational sociology has the greatest difficulty in analyzing, not the structural features of static networks, whether these be cultural, social structural, or social psychological, but rather, the dynamic processes that transform those matrices of transactions in some fashion. Even studies of ‘processes-in-relations,’ in other words, too often privilege spatiality (or topological location) over temporality and narrative unfolding” (305). The difficulty graphs have in rendering dynamics is probably the reason why none of the diagrams appearing in the foundational texts of ANT are networks (see, for instance, Callon 1986; Latour et al. 1992; Law and Callon 1992). To be sure, it is not that graph mathematics is not interested in dynamics. On the contrary, movement has always been one of the major preoccupations of network analysts. After all, Euler (1736) invented graph mathematics precisely to solve the problem of moving through the city of Konigsberg and the core application of network theory is the management of flows (the routing of trains first and of communication soon after). Yet, movement in graph theory is usually movement *through* networks and not movement *of* networks. Rooted deep in graph mathematics is the separation between what flows (ideas, goods, signals, etc.) and what stays (the structure of connections) (Madsen 2015).

This separation is highly problematical for ANT, which has always denied the existence of a “context” in which action will take place. In ANT (which, it is worth to remember, is a sociology of translation, not of transport), networks are *not* conceptualized as systems of routes through which actors drive their way. Quite the opposite: they are the maze of trails left by children running through the uncut grass. It is the runner who makes the trail, not the other way around. This is yet another reason why actor-network theorists have been uncomfortable with the graph topography and why, for instance, John Law and Annemarie Mol (Mol and Law 1994; Law and Mol 2001) propose to replace networks with “fluid spaces” and “fire spaces,” respectively characterized by the constant transformation and the constant overflowing of boundaries.

Being Sensitive to the Difference in the Density of Association

So is this it? Should we declare the case closed, divorce network analysis from ANT, and renounce exploiting the traceability of digital networks? We think not. We believe that there is a more positive (though admittedly riskier) answer to the question posed in the title of this chapter. To formulate it, one must gauge the potential equivalence among the three notions of “network” in a less literal way. No, graphs do not resemble actor-networks. As the pipe painted by Magritte does not resemble its referent (Foucault 1983), so the relations between the Bush and the bin

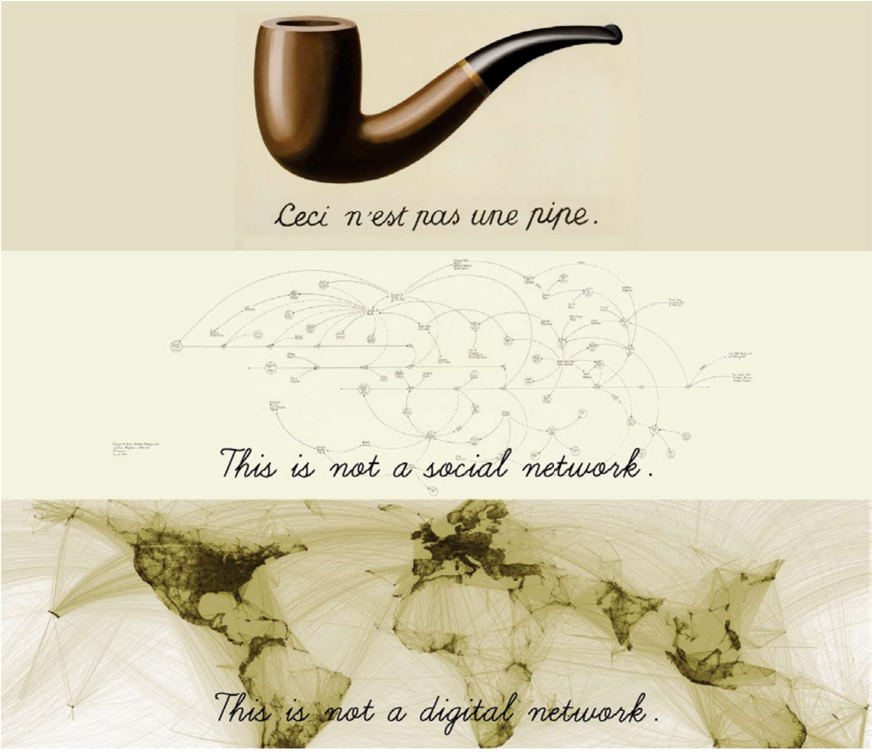

FIGURE 1: a. René Magritte, *La Trahison des images* (1928). b. Marc Lombardi, "George W. Bush, Harken Energy, and Jackson Stephens, ca. 1979–90" (1999). c. Paul Butler, "Visualizing Friendship" (2010). Captions for b and c added by the authors.

Laden families designed by Mark Lombardi or the Facebook connections designed by Paul Butler do not resemble the phenomena that they portray (see figure 1).

Social networks are not made of lines on canvas, digital networks are not made of pixels, and neither is made of data. Actor-networks are made of flesh and fabric, of words and memories, of contracts and laws, of money and transactions, and, increasingly, of cables and protocols. It is not surprising that graphs do not resemble them. And yet, this does not mean that graphs cannot help us understand collective topologies. If there is something that STS observed over and over, it is that scientific representations do not have to resemble to their referent to be useful.

Abandoning the benchmark of resemblance is important because it allows us to put aside the differences between graphs and actor-networks and consider their similarities. A first reason for SNA and ANT to be good friends is that they both fight the same assumptions of classic sociology. Their "networks" may not be synonyms, but their antonym is the same.

Both of these approaches reject a priori reifications such as "the social" or "society"; instead, these notions are constructions out of social enmeshing and become observable only ex post. Both resist reference to the representational or the symbolic; instead, they focus their empirical analyses on material reality and the meanings actors themselves ascribe to it in struggles and controversies. Both of these approaches consider the production of meaning as an activity of connecting/disconnecting and analyze how actors come to be created through collaborations of other actors in different contexts. The stories actors tell make the links between them explicit. For both approaches, the ties precede the nodes (Mutzel 2009, 878).

ANT and network analysis are both inspired by the same relational thinking (Emirbayer 1997), whose first tenet is the refusal of any form of substantialism (Robinson 2014). For both ANT and SNA, associations (and dissociations) are the only things that matter. John Law (1999; but see also Blok 2010) described this opposition by contrasting "topographical" and "topological" approaches and suggested to "imagine actor-network theory as a machine for waging war on Euclideanism: as a way of showing, inter alia, that regions are constituted by networks" (7).

But there is more. While graphs and actor-networks do not resemble each other, they bear a distinct correspondence: "A diagram of a network, then, does not look like a network but maintain the same qualities of relations—proximities, degrees of separation, and so forth—that a network also requires in order to form. Resemblance should here be considered a resonating rather than a hierarchy (a form) that arranges signifiers and signified within a sign" (Munster 2013, 24). The easiest way to understand the way in which networks resonate with collective phenomena is to consider the drawing of social networks. Of all the techniques associated with graph analysis, the ones developed to *visualize* networks are those that most closely resonate with ANT. It is not accidental that while graphs had been around for more than two centuries (Euler 1736), it was only when sociologists seized upon them that visualization joined computation as an analytical tool.

Jacob Moreno, the founder of SNA (see Moreno 1934), is formal about the importance of visualization:

> If we ever get to the point of *charting* a whole city or a whole nation, we would have an intricate maze of psychological reactions which would *present* a *picture* of a vast solar system of intangible structures powerfully influencing conduct, as gravitation does bodies in space. Such an *invisible* structure underlies society and has in influence in determining the conduct of society as a whole. . . . Until we have at least determined the nature of these fundamental structures which form the networks, we are working *blindly* in a hit-or-miss effort to solve problems which are caused by group attraction, repulsion and indifference. (*New York Times* 1933, emphasis added)

The interest for network visualization has recently surfaced again in both academic and popular culture. Images of networks are sprouting everywhere. They decorate buildings and objects; they are printed on T-shirts and posters; they colonize the desktop of our computers and the walls of our airports. Networks have become the emblem of modernity, the very form of its imagination. In part, of course, this is linked to the success of digital networks, but there is something else. Something connected to the *figurative power* of network visualization.

This *something*, we believe, is directly connected to the way networks are designed. Although several techniques for "network spatialisation" exist, a family of algorithms has progressively emerged as a standard for graph visualization: the so-called "force-directed layouts" (or "force-vectors"). A force-vector layout works following a physical analogy: nodes are given a repulsive force that drives them apart, while edges work as springs binding the nodes that they connect. Once the algorithm is launched, it changes the disposition of nodes until reaching the equilibrium that guarantees the balance of forces.

At equilibrium, force-vectors not only minimize line crossings, but also give sense to the disposition of nodes in space. In a force-spatialized network, spatial distribution becomes meaningful: groups of nodes are closer the more they are directly or indirectly connected (Jacomy et al. 2014). As proved in Noack (2009), visual clustering in force-spatialized networks is directly equivalent to clustering by modularity. In force-directed layout, "centrality," "betweenness," "diameter," "density," "structural separation," all these concepts (and many others) found a graphical equivalent (Venturini et al. 2014). They can be not only calculated, but also *seen*. This is where the figurative power of networks, their *un-resembling resonance*, comes from. This is also where the deepest bond between SNA and ANT is to be found.

Looking at a force-spatialized network provides a visual experience of *both* the metrics of network analysis *and* the notions of ANT—thus revealing their *elective affinity* (Jensen et al. 2014). Consider, for example, the notion of "boundary," which has long been a puzzle for SNA (Laumann et al. 1989). "Networks are interesting but difficult to study because since real-world network lack convenient natural boundaries. When a network as a whole is impracticably large, the usual procedure is to arbitrarily delimit a subgraph and treat it as a representative sample of the whole network. Unfortunately, this procedure is hazardous not only qualitatively . . . but quantitatively as well" (Barnes 1979, 416). On the other hand, ANT has been often accused of dissolving all the classic distinctions of social theory (micro/macro, science/politics, science/technology, nature/culture, etc.), without replacing them with any clear analytic framework. Yet ANT is not a night where all cows are black. If it is true that, following the actors and their relations, we rarely encounter clear-cut boundaries, it also true that we do experience *variations in the density of association*. Our collective existence is a "small world" (Milgram 1967; Watts and Strogatz 1998) where everything is connected. And yet, the density of associations is not homogeneous. This *in*homogeneity is manifest in spatialized networks: nodes and edges do not dispose regularly—some of them flock together, while others repulse each other. The visual space of graphs as the conceptual space of actor-network *is continuous but not uniform*. It is because of this similarity that networks can be used to represent actor-networks, despite the differences that separate them.

After all, we might be talking about the same networks.

Works Cited

Adamic, L. A., and Natalie Glance. 2005. "The Political Blogosphere and the 2004 US Election: Divided They Blog." In *Proceedings of the 3rd International Workshop on Link Discovery*, 36–43. New York: ACM. doi:10.1145/1134271.1134277.

Archer, Margaret S. 1995. *Realist Social Theory: The Morphogenetic Approach*. Cambridge: Cambridge University Press.

Barabási, Albert-László. 2002. *Linked: The New Science of Networks. How Everything Is Connected to Everything Else and What It Means for Business, Science, and Everyday Life*. Cambridge, MA: Perseus Books.

Barnes, John A. 1979. "Network Analysis: Orienting Notion, Rigorous Technique, or Substantive Field of Study." In *Perspectives on Social Network Research*, edited by W. Paul Holland and Samuel Leinhardt, 403–23. New York: Academic Press.

Barney, Darin. 2004. *The Network Society*. Cambridge: Polity.
Bateson, Gregory. 1972. "Form, Substance, and Difference." In *Steps to an Ecology of Mind*, 454–71. Chicago: University of Chicago Press.
Blok, Anders. 2010. "Topologies of Climate Change: Actor-Network Theory, Relational-Scalar Analytics, and Carbon-Market Overflows." *Environment and Planning D: Society and Space* 28 (1): 896–912. doi:10.1068/d0309.
Borra, Erik, Esther Weltevrede, Paolo Ciuccarelli, Andreas Kaltenbrunner, David Laniado, Giovanni Magni, Michele Mauri, Richard Rogers, and Tommaso Venturini. 2014. "Contropedia—The Analysis and Visualization of Controversies in Wikipedia Articles." In *OpenSym 2014 Proceedings*, 34. New York: ACM.
Boullier, Dominique, and Maxime Crépel. 2012. "Biographie D'une Photo Numérique et Pouvoir Des Tags: Classer/Circuler." *Anthropologie Des Connaissances* 7 (4): 785–813.
Burt, Ronald S. 1980. "Models of Network Structure." *Annual Review of Sociology* 6:79–141. doi:10.1146/annurev.so.06.080180.000455.
——. 1995. *Structural Holes: The Social Structure of Competition*. Cambridge, MA: Harvard University Press.
Callon, Michel. 1984. "Some Elements of a Sociology of Translation: Domestication of the Scallops and the Fishermen of St Brieuc Bay." *Sociological Review* 32 (S1): 196–233.
——. 1986. "The Sociology of an Actor-Network: The Case of the Electric Vehicle." In *Mapping the Dynamics of Science and Technology*, edited by Michel Callon, John Law, and Arie Rip, 19–34. London: Macmillan.
Callon, Michel, and Bruno Latour. 1981. "Unscrewing the Big Leviathans: How Do Actors Macrostructure Reality?" In *Advances in Social Theory and Methodology. Toward an Integration of Micro and Macro Sociologies*, edited by Karin Knorr Cetina and Aron Cicourel, 277–303. London: Routledge.
Cambrosio, Alberto, Peter Keating, and Andrei Mogoutov. 2004. "Mapping Collaborative Work and Innovation in Biomedicine: A Computer Assisted Analysis of Antibody Reagent Workshops." *Social Studies of Science* 34:325–64.
Castells, Manuel. 2000. *The Rise of the Network Society*. Oxford: Blackwell.
Chavalarias, David, and Jean Philippe Cointet. 2013. "Phylomemetic Patterns in Science Evolution—The Rise and Fall of Scientific Fields." *PLOS ONE* 8 (2). doi:10.1371/journal.pone.0054847.
Eisenstein, Elizabeth L. 1980. *The Printing Press as an Agent of Change*. Cambridge: Cambridge University Press.
Emirbayer, Mustafa. 1997. "Manifesto for a Relational Sociology." *American Journal of Sociology* 103 (2): 281–317. doi:10.1086/231209.
Euler, Leonhard. 1736. "Solutio Problematis Ad Geometriam Situs Pertinentis." *Commentarii Academiae Scientiarum Petropolitanae*, no. 8: 128–40.
Everett, Martin, and Stephen Borgatti. 2014. "Networks Containing Negative Ties." *Social Networks* 38:111–20. doi:10.1016/j.socnet.2014.03.005.
Foucault, Michel. 1983. *This Is Not a Pipe*. Berkeley: University of California Press.
Garfield, Eugene. 1979. "Citation Analysis." *Scientometrics* 1 (4): 359–75.
Giddens, Anthony. 1984. *Constitution of Society: Outline of the Theory of Structuration*. Berkeley: University of California Press.
Granovetter, Mark. 1979. "The Theory-Gap in Social Network Analysis." In *Perspectives on Social Research*, edited by P. Holland and S. Leinhardt, 501–18. New York: Academic Press.
Jacomy, Mathieu, Tommaso Venturini, Sebastien Heymann, and Mathieu Bastian. 2014. "ForceAtlas2, a Continuous Graph Layout Algorithm for Handy Network Visualization Designed for the Gephi Software." *PLOS ONE* 9 (6): e98679. doi:10.1371/journal.pone.0098679.
Jensen, T. E., A. K. Munk, A. K. Madsen, and A. Birkbak. 2014. *Expanding the Visual Registers of STS. Visualization in the Age of Computerization*. New York: Routledge.
Knorr Cetina, Karin. 1995. "Laboratory Studies, the Cultural Approach to the Study of Science." In *Handbook of Science and Technology Studies*, edited by Sheila Jasanoff, Gerald E. Markle, James C. Peterson, and Trevor J. Pinch, 140–66. London: Sage.
Latour, Bruno. 1998. "Thought Experiments in Social Science: From the Social Contract to Virtual Society." Virtual Society? Annual Public Lecture, Brunel University, London, April 1.
——. 1999. "On Recalling ANT." In *Actor Network and After*, edited by John Law and John Hassard, 15–25. Oxford: Blackwell.
——. 2010. "Networks, Societies, Spheres: Reflections of an Actor-Network Theorist." Keynote address to the International Seminar on Network Theory: Network Multidimensionality in the Digital Age,

Annenberg School for Communication and Journalism, Los Angeles. https://hal-sciencespo.archives-ouvertes.fr/hal-00972865.

Latour, Bruno, Pablo Jensen, Tommaso Venturini, Sébastian Grauwin, and Dominique Boullier. 2012. "'The Whole Is Always Smaller Than Its Parts': A Digital Test of Gabriel Tardes' Monads." *British Journal of Sociology* 63 (4): 590–615. doi:10.1111/j.1468-4446.2012.01428.x.

Latour, Bruno, Philippe Mauguin, and Geneviève Teil. 1992. "A Note on Socio-technical Graphs." *Social Studies of Science* 22 (1): 33–57.

Laumann, Edward, Peter Marsden, and David Prensky. 1989. "The Boundary Specification Problem in Network Analysis." In *Research Methods in Social Network Analysis*, edited by Linton C. Freeman, Douglas R. White, and Antone Kimball Romney, 61–79. Fairfax, VA: George Mason University Press.

Law, John. 1999. "After ANT: Complexity, Naming and Topology." In *Actor Network and After*, edited by John Law and John Hassard, 1–14. Oxford: Blackwell.

Law, John, and Michel Callon. 1992. "The Life and Death of an Aircraft: A Network Analysis of Technical Change." In *Shaping Technology/Building Society: Studies in Sociotechnical Change*, edited by Wiebe Bijker and John Law, 21–52. Cambridge, MA: MIT Press.

Law, John, and Annemarie Mol. 2001. "Situating Technoscience: An Inquiry into Spatialities." *Environment and Planning D: Society and Space* 19:609–21. doi:10.1068/d243t.

Leydesdorff, Loet. 1998. "Theories of Citation?" *Scientometrics* 43 (1): 5–25. doi:10.1007/BF02458394.

Leydesdorff, L., and P. Wouters. 1999. "Between Texts and Contexts: Advances in Theories of Citation? (A Rejoinder)." *Scientometrics* 44:169–82. doi:10.1007/BF02457378.

Madsen, A. K. 2015. "Tracing Data—Paying Attention." In *Making Things Valuable*, edited by M. Kornberger, L. Justesen, A. K. Madsen, and J. Mouritsen, 257–78. Oxford: Oxford University Press.

Marres, Noortje. 2012a. "On Some Uses and Abuses of Topology in the Social Analysis of Technology." *Theory, Culture & Society* 29 (4–5): 288–310.

———. 2012b. "The Redistribution of Methods: On Intervention in Digital Social Research, Broadly Conceived." *Sociological Review* 60:139–65. doi:10.1111/j.1467-954X.2012.02121.x.

Marres, Noortje, and Caroline Gerlitz. 2015. "Interface Methods: On Some Confluence between Sociology, STS and Digital Research." *Information, Communication & Society* 64:21–46.

Marres, Noortje, and Richard Rogers. 2005. "Recipe for Tracing the Fate of Issues and Their Publics on the Web." In *Making Things Public*, edited by Latour Bruno and Peter Weibel, 922–35. Karlsruhe: ZKM.

Milgram, Stanley. 1967. "The Small World Problem." *Psychology Today* 2 (1): 60–67.

Mol, A., and J. Law. 1994. "Regions, Networks and Fluids: Anaemia and Social Topology." *Social Studies of Science* 24 (4): 641–71. doi:10.1177/030631279402400402.

Moreno, Jacob. 1934. *Who Shall Survive?* Washington, DC: Nervous and Mental Disease Publishing.

———. 1953. *Who Shall Survive?* 2nd ed. New York: Beacon House.

Munk, Anders Kristian. 2013. "Techno-Anthropology and the Digital Natives." In *What Is Techno-Anthropology?*, edited by L. Botin and T. Borsen. Aalborg: Aalborg University Press. http://forskningsbasen.deff.dk/Share.external?sp=S2eb954fb-fb8c-46df-b850-fc1ffa3bb4e4&sp=Saau.

Munster, Anna. 2013. *An Aesthesia of Networks: Conjunctive Experience in Art and Technology*. Cambridge, MA: MIT Press.

Mutzel, S. 2009. "Networks as Culturally Constituted Processes: A Comparison of Relational Sociology and Actor-Network Theory." *Current Sociology* 57:871–87. doi:10.1177/0011392109342223.

New York Times. 1933. "Emotions Mapped by New Geography." April 3.

Noack, Andreas. 2009. "Modularity Clustering Is Force-Directed Layout." *Physical Review E* 79 (2). doi:10.1103/PhysRevE.79.026102.

Page, Lawrence, Sergey Brin, Motwani Rajeev, and Winograd Terry. 1998. "The PageRank Citation Ranking: Bringing Order to the Web." Stanford, CA: Stanford University Press.

Rieder, Bernhard. 2013. "Studying Facebook via Data Extraction: The Netvizz Application." In *Proceedings of WebSci '13: The 5th Annual ACM Web Science Conference*, 346–55. New York: ACM. doi:10.1145/2464464.2464475.

Robinson, Howard. 2014. "Substance." In *The Stanford Encyclopedia of Philosophy*, edited by Edward N. Zalta. https://plato.stanford.edu/entries/substance/.

Rogers, Richard. 2000. *Preferred Placement: Knowledge Politics on the Web*. Maastricht: Jan Van Eyck Edition.

———. 2004. *Information Politics on the Web*. Cambridge, MA: MIT Press.

———. 2013. *Digital Methods*. Cambridge, MA: MIT Press.

Rogers, Richard, and Noortje Marres. 2000. “Landscaping Climate Change: A Mapping Technique for Understanding Science and Technology Debates on the World Wide Web.” *Public Understanding of Science* 9:141–63. doi:10.1088/0963-6625/9/2/304.
———. 2002. “French Scandals on the Web, and on the Streets: A Small Experiment in Stretching the Limits of Reported Reality.” *Asian Journal of Social Science* 66:339–53.
Roth, Camille, and Jean-Philippe Cointet. 2010. “Social and Semantic Coevolution in Knowledge Networks Epistemic Networks.” *Social Networks* 32 (1): 16–29.
Van Dijk, Jan. 1999. *The Network Society*. London: Sage.
Venturini, Tommaso. 2010. “Diving in Magma: How to Explore Controversies with Actor-Network Theory.” *Public Understanding of Science* 19 (3): 258–73. doi:10.1177/0963662509102694.
———. 2012. “Building on Faults: How to Represent Controversies with Digital Methods.” *Public Understanding of Science* 21 (7): 796–812. doi:10.1177/0963662510387558.
Venturini, Tommaso, and Daniele Guido. 2012. “Once Upon a Text: An ANT Tale in Text Analysis.” *Sociologica* 3. doi:10.2383/72700.
Venturini, Tommaso, Mathieu Jacomy, and Débora Carvalho Pereira. 2015. “Visual Network Analysis.” www.tommasoventurini.it/wp/wp-content/uploads/2014/08/Venturini-Jacomy_Visual-Network-Analysis_WorkingPaper.pdf.
Venturini, Tommaso, Nicolas Baya Laffite, Jean-Philippe Cointet, Ian Gray, Vinciane Zabban, and Kari De Pryck. 2014. “Three Maps and Three Misunderstandings: A Digital Mapping of Climate Diplomacy.” *Big Data & Society* 1 (2). doi:10.1177/2053951714543804.
Vinck, Dominique. 2012. “Accessing Material Culture by Following Intermediary Objects.” In *An Ethnography of Global Landscapes and Corridors*, edited by Loshini Naidoo, 89–108. London: Intech.
Watts, Duncan J., and Steven H. Strogatz. 1998. “Collective Dynamics of ‘Small-World’ Networks.” *Nature* 393 (6684): 440–42.
White, Harrison. 2000. “Toward Ego-Centered Citation Analysis.” In *The Web of Knowledge*, edited by B. Cronin and H. B. Atkins, 475–96. Medford, NJ: Information Today.
Woolgar, Steve. 2002. *Virtual Society. Technology, Cyberbole, Reality*. Oxford: Oxford University Press.

APPENDIX F. UNBLACKBOXING GEPHI

This article has been submitted to *Science as Culture*

Jacomy, M. and Jokubauskaitė, E. (under review in *Science as Culture*) 'Unblackboxing Gephi: How user cultures shape their scientific instruments'.

Unblackboxing Gephi: How user cultures shape their scientific instruments

Abstract. Network visualization tools are blamed for being black boxes, but blackboxing has two faces. The first blames opacity (inaccessibility of the method) while the other blames transparency (invisibility of the method). We focus on Gephi, a network visualization tool popular in the social sciences and humanities, addressing its criticism as a black box, in the hope of proposing solutions. By analyzing empirical material from participant observation, interviews, and a publication review, we find that Gephi's blackboxing problem is a transparency issue. We observe that beginners are prone to producing unquestioned visualizations, using methodological shortcuts in time-constrained situations. Our investigation leads us to acknowledge the existence of an epistemic subculture around Gephi. We contend that Gephi's black box materializes less in the software than in cultural artifacts such as online documentation and tutorials. Analyzing Gephi as a mediation, we find that it influences its users by shifting their goals, and that symmetrically, its users also shift the tool's goals. Gephi influences users by making it easy to produce unquestioned visualizations, by allowing an epistemic surplus. Symmetrically, users influence Gephi by framing it as an image production device, which was not the intention of its designers.

Introduction

Digital tools and data are often said to have transformed the production of knowledge in the social sciences and humanities (Savage and Burrows, 2007; Berry, 2011; Manovich, 2013; Ruppert *et al.*, 2013; Meyer & Schroeder, 2015; Masson, 2017). However, digital tools and practices are rarely given an active role in the narratives about big data, neither from enthusiasts (e.g. Lazer *et al.*, 2009) nor from critics (e.g. Boyd and Crawford, 2012; Ruppert *et al.*, 2013). The discussion tends to be about technology rather than tools (or instruments, as we will refer to them). Most authors agree on the material-semiotic nature of big data issues, yet the level where materiality can be directly observed, the instrument level, is rarely addressed. This is surprising, considering that computerized tools are constantly suspected of shaping our scientific practices. The premise of this paper is to focus on a given scientific instrument (Gephi), and address its criticism (being a black box) by studying the practices of researchers, in order to propose improvements.

All tool criticism stems from the observation that tools are not neutral. Informing that fact with their own practice and drawing from multiple theoretical perspectives, scholars from different disciplines have reflected on the instruments they use. In the humanities, Drucker defends the “performative dimension of materiality” (2013); in new media studies, digital methods experiment with digital devices (Rieder, 2013; Rogers, 2013) and account for their biases (Marres, 2017), their uses and abuses (Marres, 2012), and the “lack of awareness of the layers of mediation” involved in them (Rieder and Röhle, 2017). Also in new media studies, van Es et al. advocate for “a rigorous inquiry into the tools used for research” they dubbed “tool criticism” (2018). Although non exhaustive, this list highlights a common argument that calls back to the notion of technological determinism: tools influence us through inevitable biases that we must assess in a science setting.

In this article we focus on a specific network analysis and visualization tool called Gephi (see figure 1). In the social sciences and humanities (SSH) we find criticism of both this kind of tool, i.e. data visualization instruments (e.g. Haraway, 1988; Drucker, 2011), and this tool in particular (e.g. Masson, 2017; Rieder and Röhle, 2017). This criticism mainly points at the way visualization elicits self-evidence. The argument goes as follows: Tools lead researchers to overlook the layers of mediation involved in them, thus failing to account for their effect on the method; as the distortion is dismissed, the visualization is conflated with the phenomenon, compromising reproducibility and interpretability. Using this criticism as a starting point, we investigate where and how this kind of influence is enacted, in order to find possible countermeasures.

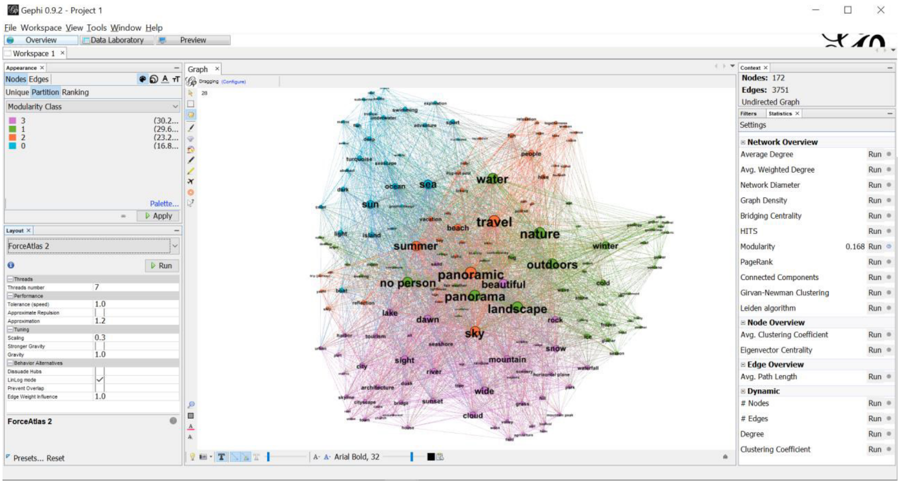

Figure 1 - A screenshot of Gephi. Network visualization is at the center of the user interface. On the left, the settings of a layout algorithm. On the right, a list of metrics that one can compute.

Gephi is accused of being a *black box*. This concept is central in tool criticism. The common sense suggests that, as the scientific method requires scrutiny, the instruments employed must be held accountable, as in “opening the black box.” However, another version of the *black box* exists within Science and Technology Studies (STS). It refers instead to “the way scientific and technical work is made invisible by its own success” (Latour, 1999, p. 304). The coexistence of these two versions causes a great deal of confusion. Indeed, the first version blames *opacity* (inaccessibility of the method), while the second blames *transparency* (invisibility of the method). These terms are misleading, because the two understandings are not as antagonistic as the opaque/transparent dichotomy suggests. As articulating them is tricky, most critics tend to focus on one meaning, excluding the other one. This is problematic, as mitigating blackboxing *by opacity* and *by transparency* requires different solutions. Clarifying the situation is a secondary goal of this paper, and a necessary step. We diagnose Gephi’s problem as blackboxing by transparency.

Our main argument contends that Gephi’s blackboxing mostly materializes outside of the tool, within the practices of people using it, and their culture. The importance of culture is nothing new. Rieder and Röhle have made this argument twice (2012, 2017), illustrating it with Gephi. They propose the notion of “digital *Bildung*”[i] (2017) as a response to its blackboxing. Like them (2017, p.110), we adopt an “anti-essentialist approach,” refusing to “cede to simple oppositions” such as qualitative/quantitative, opaque/transparent, expert/profane, or designer/user. We just follow the problem wherever it happens to be. We retrace the materiality of Gephi’s blackboxing effect by analyzing articles, interviews, and participant observation during workshops; and we find that tutorials, articles, and online discussions matter more than the software itself. We argue that through the production of cultural artifacts, the community of Gephi users is in the position of co-designing the instrument along with its actual developers. This dynamic is not surprising, but the relative insignificance of the instrument's materiality is. Indeed, it completely changes our initial perspective: if the software is not the main cause of blackboxing, then how to address the issue?

The unexpected finding of our study is the realization that a specific subculture has emerged around Gephi. Our findings challenge the idea that blackboxing is a tool maker's problem: the user community is a major part of it. Remarkably, this subculture is partially misaligned with the intent of Gephi's creators. It does not have the same goals, it repurposes the tool in unintended ways, and it has its own way of valuing visualizations. We document this dynamic, and we discuss it by drawing from Latour and Akrich's theory of mediation. We propose the idea that Gephi, as a mediation, influences its users by shifting their goals, and that symmetrically, the users also shift the tool's goals. Ultimately, we diagnose Gephi's blackboxing problem as a by-product of the interplay between the instrument and its epistemic subculture, which can better be solved by intervening on cultural artifacts than its source code.

We start by presenting Gephi, followed by analytical perspectives, summarizing the main criticism of Gephi and similar tools from the social science and humanities, clarifying the two versions of blackboxing, and introducing Knorr Cetina's notions of *laboratory* and *epistemic culture*. We present our methodology, then we showcase our empirical observations in two steps. Firstly, we investigate the kind of blackboxing problem Gephi has, and we find that it is mostly criticized for being too transparent. Secondly, we retrace the materiality of Gephi's blackboxing problem, which leads us to acknowledge the existence of a specific subculture. Finally, we discuss Gephi as a technical mediation, and we conclude on suggestions to fix Gephi's blackboxing problem.

The case of Gephi

The instrument this research focuses on is Gephi (Bastian *et al.*, 2009), an open source software tool for network analysis and visualization. It operates via a number of embedded algorithms (e.g. Blondel *et al.*, 2008; Jacomy *et al.*, 2009) and a graphical user interface (see figure 1). In practice, it allows users to visualize a relational data set (a network) and execute different analytical tasks, such as computing statistics or filtering data. It has been referenced in more than five thousand papers[ii] across a variety of disciplines, inside and outside the social science and humanities. Its popularity within the SSH has lead it to be discussed from that perspective (Grandjean and Jacomy, 2019; Wieringa *et al.*, 2019), in addition to a more general discussion, in computer science and information design, on the kind of visualizations it provides (Gibson *et al.*, 2012; Krzywinski *et al.*, 2012; Dunne *et al.*, 2015; Munzner, 2015).

Gephi's most popular node placement algorithm, *Force Atlas 2*, has become an increasingly important part of contemporary network analysis. Algorithms of this type (i.e. "force-driven") work by simulating "a physical system in order to spatialize a network. Nodes repulse each other like charged particles, while edges attract their nodes, like springs. These forces create a movement that converges to a balanced state" (Jacomy *et al.*, 2009). We have to emphasize, however, that network visualisations created this way are “not deterministic, and the coordinates of each point do not reflect any specific variable” (Jacomy *et al.*, 2009).

While popular, force-driven placement algorithms have also been extensively criticized (for an overview, see Gibson *et al.*, 2012; Dunne *et al.*, 2015), notably for their “inherent unpredictability, inconsistency and lack of perceptual uniformity” (Krzywinski *et al.*, 2012) and “brittleness” (Munzner, 2015). Additionally, due to the many parameters and user interactions that need to be taken into consideration while using Gephi, it is notoriously complicated to document, communicate and reproduce how the network visualization came into being (Wieringa *et al.*, 2019).

Analytical perspectives

The criticism of data visualization tools as too transparent in the SSH literature

Within the social sciences and humanities (SSH) we find a criticism of data visualization and its tools on the ground that **transparency elicits self-evidence**. We offer here a few non-exhaustive landmarks on the circulation of this idea in the SSH literature (see figure 2). We highlight the different takes on technological influence. You will notice that not every author assumes technological determinism, a distinction necessary to discussing their views.

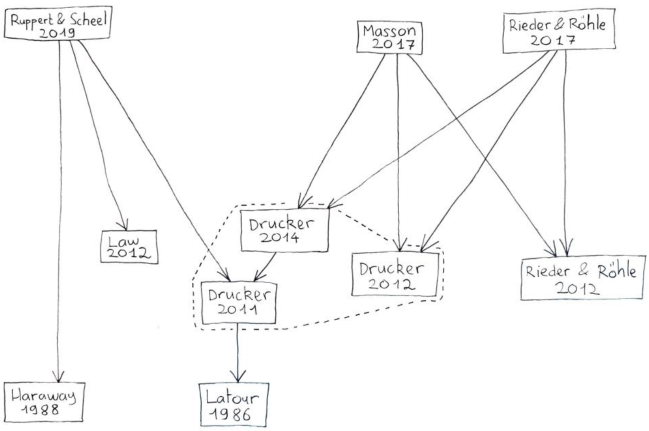

Figure 2 - A few publications criticizing data visualization and its tools for their transparency in the social science and humanities. Arrows represent citations.

When Evelyn Ruppert and Stephan Scheel (2019) account for the politics of method involving big data, they argue that the visualization becomes “not only a **vehicle** for the data, but first and foremost **for its claimed self- evidence**" (emphasis added). Here they draw on Johanna Drucker (2011), Donna Haraway (1988) (both summarized below), and on John Law's idea that "practices enact realities" (2012). Similarly, Eef Masson (2017) writes that "computational research tools **are often assigned** such values as reliability and transparency" (emphasis added), drawing on Drucker (2012, 2014) and Rieder and Röhle (2012, 2017).

Bernhard Rieder and Theo Röhle write (2017): "The problem, again, comes from the fact that tools such as Gephi have made network analysis accessible to broad audiences that happily produce network diagrams without having acquired robust understanding of the concepts and techniques the software mobilizes. This more often than not **leads to a lack of awareness of the layers of mediation** network analysis implies and thus to limited or essentialist readings of the produced outputs that miss its artificial, analytical character" (emphasis added). This argument is a refined version of a point from their 2012 paper.

Johanna Drucker writes that maps, charts and graphs "are a kind of **intellectual Trojan horse**, a **vehicle through which assumptions** about what constitutes information **swarm with potent force**. … they pass as unquestioned representations of 'what is.' This is the hallmark of realist models of knowledge and needs to be subjected to a radical critique to return the humanistic tenets of constructedness and interpretation to the fore" (emphasis added). This passage from her book *Graphesis* (2014) is also in her 2011 paper. In 2012 she also writes the same idea: "Graphs and charts reify statistical information. They give it **a look of certainty**. Only a naive viewer, unskilled and untrained in matters of statistics or critical thought, would accept an information visualization at face value" (emphasis added).

Finally, Donna Haraway writes in her influential paper *Situated Knowledges* (1988): "all seems not just mythically about the god trick of seeing everything from nowhere, but to have put the myth into ordinary practice. … **There is no unmediated photograph or passive camera obscura in scientific accounts of bodies and machines**; there are only highly specific visual possibilities, each with a wonderfully detailed, active, partial way of organizing worlds" (emphasis added). The "situated knowledges" she proposes are precisely a way to reclaim the power accaparated by self-evidence.

Here, transparency is criticized on two different grounds. Firstly, the material-semiotic properties of the apparatus enact self-evidence, which leads to dismissing its methodological influence. This understanding of influence is technological-deterministic. Secondly, self-evidence is enabled by practices and plays a rhetorical role in the politics of method. This influence does not assume technological determinism. These two forms of influence are cumulative but also independent. They can coexist, yet some authors only state one or the other: Drucker's point is deterministic, while Ruppert and Scheel's one is not. The distinction will matter at the end of this paper, when we discuss Gephi as a technical mediation. For the moment, it suffices to keep in mind that this criticism points to two different things: the tool's materiality, and the social interplay with it. Therefore, addressing this criticism may require intervening in two different places.

Two versions of blackboxing: by transparency, and by opacity

Bruno Latour argues that blackboxing is “the way scientific and technical work is made invisible by its own success. When a machine runs efficiently, when a matter of fact is settled, one need focus only on its inputs and outputs and not on its internal complexity. Thus, paradoxically, the more science and technology succeed, the more opaque and obscure they become.” (1999, p. 304). It corresponds to what Paßmann and Boersma (2017) call *practical transparency*, when the user “does not have to be bothered with the underlying machinery or software” as Star et al. put it (2003, p. 242). We call this version *blackboxing by transparency*, because it often concerns a mediation, something that works on the condition that it is transparent, such as eyeglasses (in a literal sense) or the computer mouse (metaphorically). Here we draw on Maurice Merleau-Ponty’s (1962) notion of *embodiment*. As he argues, one stops perceiving the mediation as an object, and instead perceives *through it* as if it were part of one’s body (his classic example is the blind man’s stick); transparency refers here to this *through*.

The alternative, that we call *blackboxing by opacity*, addresses the impossibility to know the method, as in the colloquial expression “opening the black box.” Latour attributes this version to cyberneticians, who use it “whenever a piece of machinery or a set of commands is too complex ... . That is, no matter how controversial their history, how complex their inner workings, how large the commercial or academic networks that hold them in place, only their input and output count.” (2000, p. 681) Such black boxes are opaque by design. *Blackboxing by opacity* is one of the wider-known points of tool criticism in academia, especially in the social sciences. Rieder and Röhle characterize it as the “practical [im]possibility to access the most obvious layer of functional specification, a tool’s source code” (2017, p. 113), hindering “our ability to understand the method, to see how it works, which assumptions it is built on, to reproduce and criticise it” (2017, p. 112). This blackboxing opposes what Paßmann and Boersma (2017) call *formalized transparency*, the ability to access methodological information.

The coexistence of these two versions creates confusion. We can nevertheless clarify the question of transparency. In *blackboxing by transparency*, the tool itself is transparent, because it acts as a mediation. Here transparency blackboxes because it conceals the existence of methodological effects. The user does not even try to understand the method, because it ignores that a method is at play. In *blackboxing by opacity*, the opacity of the tool is a metonymy; in fact it is the method that is opaque. The existence of methodological effects is known, but the access to relevant knowledge is blocked. These two dimensions are independent: a tool may or may not work as a transparent mediation, and knowledge on its method may or may not be accessible. But as we will argue in the discussion section, following Latour (1994), using a tool requires some degree of blackboxing since transparency is necessary to its operation; yet the same tool may get unblackboxed in a different context once it is no longer in use.

We will see that Gephi is transparent in both senses: it is efficient enough as a mediation, and its methodological ground is exposed. Our observations confirm the criticism from SSH, pointing to a problem of *blackboxing by transparency*.

Gephi's epistemic subculture

According to Knorr Cetina, "[e]pistemic cultures are cultures that create and warrant knowledge" (1999, p. 26). In her own words, the notion of epistemic culture "disrupts the idea of the epistemic unity of the sciences and suggests that the sciences are in fact differentiated into cultures of knowledge that are characteristic of scientific fields or research areas, each reflecting a diverse array of practices and preferences coexisting under the blanket notion of science" (Knorr Cetina and Reichmann, 2015, p. 873). In the case of Gephi, as the scale is noticeably smaller, we argue an epistemic *subculture*.

Still following Knorr Cetina (1999), this paper positions the use of Gephi in the *laboratory* of SSH. Differently from a physical understanding of a laboratory, she defines it rather by the action of working with inscriptions produced by *inscription devices* as opposed to studying objects in "nature". Latour and Woolgar (1986) introduce the notion of *inscription device* as "any item of apparatus or particular configuration of such items which can transform a material substance into a figure or diagram which is directly usable" (p. 51). Gephi itself is an inscription device, but it is not the only one appropriated by its own subculture. We also account for dedicated informational spaces (e.g. a Facebook group[iii]) where beginners can find guidance, and a set of resources considered standard. A plethora of network analyses with Gephi, altogether good and bad, are also available online.

The notion of epistemic subculture is notably useful to retrace the "Gephi method" (e.g. Hemsley and Palmer, 2016), a notion convoked by users as a ground for their network analysis, or to address Gephi's influence. We argue that the "Gephi method" only exists in Gephi's subculture: it is not enforced by the tool; it is stated neither in its official documentation, nor in academic publications; it only circulates in the community as an informal set of guidelines and recipes, and appears as an *a posteriori* label for potentially any network analysis involving Gephi. The web, and not Gephi's software, is the apparatus where the "Gephi method" is inscribed.

Methodology

This paper is a collaboration around the material collected by one of the authors, Emilija Jokubauskaite, more extensively presented in her master's thesis (2018). It contrasts the voice of users with Mathieu Jacomy's designer and developer perspective on Gephi, to unpack the different dimensions of blackboxing. In that sense, it largely draws on the tradition of critical technical practice (Agre, 1997; see also van Es and Schäfer, 2017).

We engaged in participant observation in a dozen of Gephi workshops over the last decade, often as trainers, and sometimes as trainees. We conducted and inductively analyzed semi-structured interviews with 6 Gephi users of varying levels of experience, who were chosen due to having conducted work that utilises it for academic purposes within media and communication studies. It consists of a number of open-ended questions aimed at understanding how researchers communicate their usage of the tool and how they represent the method. Parts of each interview followed an elicitation interviewing method (Johnson *et al.*, 2002): the interviewees were asked to use Gephi to briefly interact with a data sample (either familiar or new to them) prior to the interview and take notes on their use of the tool. During the interview, the tools' graphical user interface was open and the interviewees narrated their methodological steps of using it, followed by a discussion of the decision making process, questions about starting to use the tool and overall experience as well as reflections on Gephi use in the academic field in general and other topics.

To triangulate the information gathered from the interviews with the methodologies presented in the documentation, we also analyzed 17 published academic papers. The papers were chosen through a systematic sampling, including recent papers from 2009 up to 2018, filtering 50-100 papers published each year for those of most relevance to the area of social media research in media and communication studies.

Conducted interviews	**Analyzed academic papers**
[1] Pre-PhD researcher	**[8]** Friendfeed Breaking News: Death of a Public Figure (Magnani *et al.*, 2010)
[2] MA student	**[9]** Understanding the Value of Networked Publics in Radio: Employing Digital Methods and Social Network Analysis to Understand the Twitter Publics of Two Italian National Radio Stations (Bonini *et al.*, 2016)
[3] PhD student, last stages of finishing the degree	**[10]** Uncovering the Wider Structure of Extreme Right Communities Spanning Popular Online Networks (O'Callaghan, 2013)
[4] MA student	**[11]** Tweeting the viewer—use of Twitter in a talk show context (Larsson, 2013)
[5] Post-PhD researcher, Communication Science field	**[12]** Triumph of the underdogs? Comparing Twitter use by political actors during two Norwegian election campaigns. (Larsson and Moe, 2014)
[6] Researcher	**[13]** Translocal Frame Extensions in a Networked Protest: Situating the #IdleNoMore Hashtag (Grundberg and Lindgren, 2015)
[7] Mathieu Jacomy, one of Gephi's creators	**[14]** The Social Ties of Immigrant Communities in the United States (Herdağdelen *et al.*, 2016)
Note: Full interview transcripts are available per request	**[15]** The Role of Emotional Stability in Twitter Conversations (Celli and Rossi, 2015)
	[16] The Rise and the Fall of a Citizen Reporter (Metaxas and Mustafaraj, 2013)
	[17] The Potential and Limitations of Twitter Activism: Mapping the 2011 Libyan Uprising (Lindgren, 2013)
	[18] The Australian Twittersphere in 2016: Mapping the Follower/Followee Network (Bruns *et al.*, 2016)
	[19] Predicting International Facebook Ties through Cultural Homophily and Other Factors (Barnett and

	Benefield, 2017)
	[20] Climate Change on Twitter: Content, Media Ecology and Information Sharing Behaviour (Veltri and Atanasova, 2017)
	[21] Crisis Communications in the Age of Social Media: A Network Analysis of Zika- Related Tweets (Hagen *et al.*, 2018)

Table 1. List of interviews and analyzed publications.

Gephi's blackboxing is a transparency issue

Here we present Gephi's blackboxing problem as painted in our empirical material. It turns out that Gephi can be perceived as opaque or transparent, depending on the user. Yet our analysis shows that the problem lies with blackboxing by transparency, and notably when it comes to beginner users.

Scholars do not fully assess Gephi's methodological dimension

As a starting point, we account for how Gephi-related methodology is featured in academic publications. Our publication review shows that authors rarely make explicit which method they use to analyze networks. Some of these publications do not present the settings employed to apply the algorithms of Gephi [e.g. 8, 12, 13, 14, 15]. In others, the explanation of methodological decisions draws on the settings of the tool [e.g. 16, 18] but their *effects* on the analysis are not discussed.

While some authors do elaborate on the method [e.g. 19, 20], their rationale does not directly relate to Gephi. An illustration of that situation can be found in the publication of Barnett and Benefield [19]. In their article, they expose and discuss the measures of in-degree centrality and betweenness centrality. Gephi is providing these statistical metrics, but is just presented as a way to illustrate the findings. Similarly, Bonini's and Celli et al.'s articles [9, 15] present the method of network analysis in the methodology section, but do not mention Gephi until a visualization is presented later in the text, somewhat separating the tool from the method. Additionally, as Axel Bruns writes, the referees for articles do not usually request such methodological information: "treatment of tools such as Gephi as black boxes whose interior operations can be ignored is not limited to scholarly authors alone" (2013), referring here to what we call blackboxing by transparency.

To better understand the rationale behind the methodological decisions with Gephi, we turn to the interview data. In them, we observe, the users explain their methodological decisions from the viewpoint of the tool, for example stating that they used Force Atlas 2, a layout algorithm, "because it is actually optimized for Gephi" [6]; "because basically it was the one that worked best" [5] or because it "is the most convenient … to use" [1]. These examples suggest that the Gephi users may be paying more attention to finding the settings that allow extracting the “correct” or “best” network visualisation, rather than rationalizing their practice based on how the method operates. For many scholars, Gephi is put to use before they fully grasp its methodological effects, which also points to blackboxing by transparency.

Gephi is transparent to some users

The interviewees reflect on the level of transparency offered by the instrument. For example, some of them state that “it gives you a very direct feedback” [1] or that they don’t necessarily know what it does, but it “gives a reasoning behind it after you run it” [2]. They also report on specifically trying out some functionalities of the tool in order to gain an understanding of them [1]. Moreover, the researchers refer to the tool as transparent, saying that “you always have sort of a clear methodological thing, that you can reference and people can look at it after” [2]. That is, the researchers appreciate that the tool provides them with references to academic literature sources, which contextualize the various metrics and functions one can apply with the tool. In many ways, then, Gephi is perceived as self-aware of blackboxing criticism. Following Paßmann’s and Boersma’s (2017) notions of *formalized* and *practical* transparencies, it may be seen as successfully providing both: by providing access to the backend of the tool (formalized), and by allowing users to understand by practicing, for instance via visual feedback (practical). Gephi is perceived here as dealing well with blackboxing by opacity. However, not all users share this feeling.

Gephi may also seem opaque

Some users report on not being sure of how certain aspects of the tool work. More specifically, they reflect on often using the tool without making the decisions consciously [1, 2, 4] and not being aware of what and why they should question in the process of implementing the tool-use in their research [2, 3]. They articulate that the instrument is “complicated and there’s a lot of things that you have no idea what is happening and what is going on” [3]. Moreover, one of the interviewees also argued that the interface does not necessarily help the user understand what is happening method-wise [4]. These observations can be complemented by Axel Bruns’ (2013) discussion of Gephi transparency, in which he argues that even though there is quite a lot of information about the technical aspects behind various algorithms in Gephi, understanding them to a needed level is often out of the skillset of humanities and social sciences scholars. The ease of putting Gephi to use contrasts with the difficulty to understand what it does exactly.

Gephi is a black box to beginners

Gephi was initially designed for the needs of the *e-Diasporas Atlas* project (Diminescu *et al.*, 2012), a collaborative exploration of the web of diasporas (on the apparatus, see Diminescu *et al.*, 2011; on the project, see Diminescu, 2012). The participating scholars were specialists of migrations inexperienced in network analysis. Gephi was largely designed for the persona of the *scholar-going-digital*: someone trained to the scientific method in general and field work in particular, and willing to extend their skills to digital methods as a complement. This design has two noteworthy consequences: Gephi takes *beginners* into account, and its purpose is *operational*. It borrows techniques from the fields of social network analysis and network science and translates them into seemingly mundane features, such as “clustering;” yet it provides the references of the publications presenting the algorithms implemented. It tries to articulate ease of use with methodological accountability, to satisfy the needs of both beginners and scholars.

Users are sensitive to this design of accountability. Interviewed researchers say, for example, that “through the time of working with the actual tool you … get to know what it … represents. So it gives you more insight into what it is … that you are working with” [1]. Moreover, several of the interviewees express a wish to do more related research in order to learn more about the tool [2, 4]. Gephi is perceived as an entry point to academic literature, but this knowledge is not required to use it.

Lemercier and Zalc, in supplemental material[iv] to their book *Quantitative Methods in the Humanities: An Introduction* (2019), warn against software that “presents some analysis tools like ‘black boxes’” and comment that “contrary to many, we are no fans of Gephi, for this type of reasons; … we do not find it well-suited to beginners.” Bernhard Rieder and Theo Röhle (2017, p. 118) voice a similar concern: “The problem … comes from the fact that tools such as Gephi have made network analysis accessible to broad audiences that happily produce network diagrams without having acquired robust understanding of the concepts and techniques the software mobilizes.” In short, Gephi is too convenient to beginners, which leads to blackboxing by transparency.

These insights suggest two takeaways. Firstly, and unsurprisingly, **Gephi’s opacity depends on its user’s training**. Experts are less prone to see it as a black box; the problem lies with beginners. Secondly, **Gephi’s perceived opacity derives from its transparency**. It is deemed too accessible to enforce the scientific standards. Indeed, Gephi is transparent enough to be used by untrained users, who find their way by trial and error, but it also involves a number of decisions perceived as arbitrary, as the users have not (yet) learned what these choices imply in terms of method. The main problem with Gephi is its blackboxing by transparency.

The black box materializes in the artifacts of Gephi’s epistemic subculture

Our observations confirm the main criticism of Gephi from the SSH: it is blackboxed *by transparency*. The argument states that Gephi enacts self-evidence, which leads to dismissing its methodological implications. As we have seen, two flavors of this argument exist, depending on whether technological determinism is assumed or not. The technological-deterministic version blames the tool (and its materiality) for self-evidence. The other one blames practices, and rhetorical games in the politics of method. In this section, we inquire into which materialities are enacting the self-evidence of Gephi’s visualizations, we investigate where the transparency problem is rooted. We find that the artifacts produced by Gephi’s subculture bear much of the responsibility for the blackboxing.

Self-evidence is enacted within user practices

As we have seen, most academic papers featuring Gephi do not provide any discussion or justification of the methodological decisions related to it [e.g. 8, 12, 13, 14, 15, 17, 21] (see also Bruns, 2013). In a number of papers, Gephi is just presented as one of the tools the analysis was conducted with [e.g. 13, 14], or even as just a tool to produce illustrations [e.g. 10, 12, 14, 15, 17, 19, 20, 21, 22, 24]. This is how Gephi is *enacted* as self-evident. Indeed, as the lack of justification becomes accepted in peer-reviewed publications, it tends to become the norm. Indeed, our interviewees [2, 4] reflect that in the cases where network analysis is deemed less central to the research, scrutinizing the use of Gephi is not necessary. One of the interviewees says that, because it is “only one tool they used” [4], there is no need to elaborate on their implementation of it. It is also worth pointing at a widespread view among researchers, that using Gephi is generally not central to their analysis, very often equating it with “just a data visualisation” [3]. These observations suggest that self-evidence arises first and foremost from the unquestioned proliferation of Gephi outputs.

It is not surprising that the circulation of network maps is determinant to their self-evidence effect. Brooke Foucault Welles and Isabel Meirelles (2014) have accounted for the similar trajectory of the network visualization from Lada Adamic and Nathalie Glance’s (2005) influential paper *Divided they Blog*. It is not through the work of its authors that this image became transparent, in the sense of (allegedly) carrying a (self-evident) scientific meaning; but through its circulation within the academic community. As Bruno Latour (1986) argues, the materiality of visualization may matter more than its semiotics, notably through its ability to circulate while maintaining its consistency (what he calls “immutable mobiles”). Our observations similarly suggest that self-evidence is not an intrinsic property of network visualizations, but emerges from their unquestioned circulation. To understand this lack of questioning, we now account more closely for the practices within Gephi’s laboratory.

Shortcut practices within Gephi’s laboratory

Following Knorr Cetina (1999), we refer to Gephi’s *laboratory* as the space where people use it as an inscription device. Of course, in this case, it is not a physical place. It is nevertheless material-semiotic, and draws a relative unity from three things: shared online spaces, a limited set of popular resources, and obviously, Gephi itself. Users share their work and seek help and advice through Twitter, a dedicated Facebook group[v], and blogs[vi]. Some official teaching material does exist (website[vii], wiki[viii]) but most of it has been authored by the community, including three books.[ix] Gephi is also part of a number of regular cursus, for instance the Digital Methods Initiative’s Winter and Summer schools[x].

Our observations suggest that the laboratory promotes a utilitarian use of Gephi, as a methodologically neutral commodity. Indeed, it is often used in a time-restricted environment. Interviewees explain that they learned how to use the tool during data sprints [1], short introductory classes [4] or project-based university courses [4, 6] and other project-to-project cases. That is, while the researchers often arrive at the use of Gephi without former knowledge of network analysis, their educational path from the beginning can be seen as largely focused on producing findings in short-time projects rather than taking the time to empirically explore networks and learn about them.

Moreover, when learning how to carry out network analysis, researchers often learn from step-by-step tutorials and “speed courses” [1] or “best practices” that increase productivity when using the tool. Following that, the researchers report being encouraged to “just use it” [3] or instructed by their peers to take some methodological steps without providing further information on why and what the implications might be [1, 4]. Consequently, the researchers refer to their use of Gephi as *automatic*, for instance “if I want a specific end result, I know how to get there, but it’s very automatic, I don’t really understand why this is what I do, it’s just that I go through the moves, because that’s what you have to do.” This situation is typical of a know-how teaching, where reproducing the actions of the trainer is the first step of the learning process. We observed trainees facing this challenge, and they have different reactions. Some are naturally driven to question the methodological implications of their actions, while others see the mere production of a network map as the main takeaway, regardless of their ability to interpret it. Not all users are drawn to such shortcuts, but those who are fail to account for the method at play. When circulating them, they cannot avoid enacting their self-evidence.

Shortcuts may be bad, they are quite ordinary. Regardless of the quality of the teaching, practical steps may be received as a recipe, a ritual. It is well known that when it comes to instruments, lessons do not replace practice. The ordinariness of shortcuts contributes to blaming Gephi for its ease of use. These observations partially match Rieder and Röhle’s (2017) conclusion that “tools such as Gephi have made network analysis accessible to broad audiences that happily produce network diagrams without having acquired robust understanding of the concepts and techniques the software mobilizes.” Indeed, we observe that practices with Gephi lead to the circulation of unquestioned network maps. Yet we challenge the idea that the problem roots in the materiality of the tool, in its design and software. So far we mentioned no reason to assume so, but it does not mean it is not the case. It is now time to assess Gephi’s blackboxing by looking directly into its design.

Gephi’s design aims at resisting blackboxing

As we have seen, Gephi’s design addresses the dual needs of the *scholar-going-digital*: ease of use, and methodological rigor. On the one hand, it supports an utilitarian usage by commoditizing network analysis (or trying to do so). On the other hand, it supports the scientific method by forcing the user to take methodologically impactful decisions that could have been automated. Gephi’s proxy paper (Bastian *et al.*, 2009) is too short to discuss its design. Fortunately, the paper of the layout algorithm *Force Atlas 2* (Jacomy *et al.*, 2014), developed by the same team, offers some elements. The authors state: “Our goal was to provide some network analysis methods to social scientists, that would not require learning graph theory.” Here, they aim at commoditization. Then the authors explain why their algorithm displays its process in real time. “Visualizing the ‘live’ spatialization is a key feature of Gephi. It provides a very intuitive understanding of the layout process and its settings. … Social scientists cannot use black boxes, because any processing has to be evaluated in the perspective of the methodology." Here, they aim at supporting methodological rigor. Their mention of "black boxes" refers to blackboxing by opacity. The creators of Gephi were aware of this pitfall, and explicitly refrained from sacrificing methodological relevance to ease of use. Gephi's design aims at resisting blackboxing by opacity.

Does Gephi's design succeed in resisting blackboxing by opacity? Gephi might inadvertently incentivize users to cut the method short. We observe that such incentives tend to come from cultural artifacts rather than the tool's own materiality. As an emblematic illustration, we assess the common idea that *Force Atlas 2* is Gephi's default layout algorithm. Indeed, the citations of the paper (Jacomy *et al.*, 2014) confirm its popularity.[xi] Yet the algorithm is not emphasized in any way in Gephi's materiality: it features as a mere item in a list; it is not selected by default; it is not the first of the list; it is not highlighted; its name does not mention "Gephi" (see figure 3). What makes it the default algorithm is not inscribed in the software, but in cultural artifacts. Its paper presents it as Gephi's "default layout algorithm." Teaching material presents it as the go-to solution. Its popularity reinforces its status of standard within the Gephi laboratory. If, as Rieder and Röhle (2017) write, "software performs a method," then the "Gephi method" mentioned by interviewees and academic publications may only materialize in the artifacts of Gephi's subculture, and not in the software. What does it mean, then, that "software performs a method"?

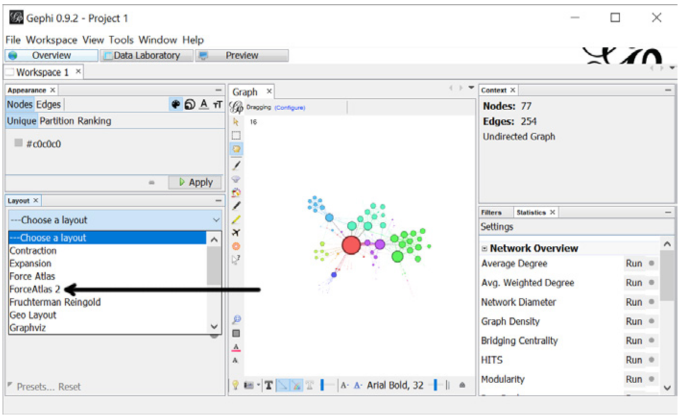

Figure 3. Force Atlas 2 is not emphasized in Gephi's graphical interface. It features in a list of algorithms you have to unfold (black arrow).

We have seen that if Gephi's ease of use encourages shortcut practices, it is not the result of a trade-off with methodology. Yet ease of use can influence users by itself, by allowing them to produce visualizations much before they had the time to digest the methodology. Gephi's design is not incentivizing them to cut short; its sin is to empower. Ease of use has obvious benefits, even though it is detrimental at the same time. Although the idea of decommoditizing Gephi has merit, it does not offer a clear program of intervention. By comparison, Gephi's laboratory is full of cultural artifacts enacting blackboxing by transparency. **The circulation of unquestioned network maps might be accepted at the moment, it does not have to be. Like any cultural norm, it can be changed.** This is where it is useful to acknowledge the existence of an *epistemic subculture* around Gephi.

Gephi's epistemic subculture

Knorr Cetina's (1999) concept of *epistemic culture* allows accounting for the observed disconnection between Gephi practices and theoretical knowledge on networks. Network analysis, as a field, offers precise ways to warrant knowledge, largely drawing from the solid foundations of social network analysis (Borgatti *et al.*, 2009). Those ways consist, for instance, of detecting topological patterns with dedicated metrics. Although we observe such practices with Gephi, we also find different ones, notably when it comes to using visualizations. Those are rarely presented *explicitly* as visual evidence, although it may happen. Most of the time they circulate as drafts or work in progress, for instance as screenshots illustrating an exploratory approach. Yet they carry an implicit meaning as inscriptions, and their circulation contributes to shape how the community warrants knowledge. As Bruns (2013) remarks, unquestioned network maps are common in academic publications, as if they required no methodological context, as if they were self-evident. Gephi does not incentivize such practices, yet it makes them possible by empowering beginners to produce network maps without acknowledging the methodological standard of network analysis. We observe that Gephi's epistemic subculture makes use of this opportunity, inadvertently inventing its own way to warrant (or legitimize) knowledge. And to be clear, here we neither contest nor endorse Gephi's epistemic subculture; we merely document it. It provides a meaningful context to the criticism of Gephi and helps situating its blackboxing problem.

Discussion: Gephi as a technical mediation

Like Rieder and Röhle, we draw on Gilbert Simondon's thinking of the technical object (1958), and more recently on Madeleine Akrich (1993) and Bruno Latour (1994). This school of thought contends the existence of a script, a program, attached to the object. In that sense, it helps formalize how self-evidence arises from the use of Gephi. Importantly, it argues that the program is neither determined by just the practices, nor just the instrument.

To reuse a distinction made by Latour (1994), there is a "materialistic" and a "sociological" reading of the argument of self-evidence. In a "materialistic" perspective, "[e]ach artifact has its script, its 'affordance'"; self-evidence is scripted in Gephi. This version emphasizes the role of material-semiotic features over practices. The materialistic view assumes technological determinism, and situates self-evidence within the software. And there is a "sociological" perspective where the tool is a "neutral carrier of will that adds nothing to the action." This version emphasizes practices and rhetorics, and puts the blame on people. As Latour notes, "the two positions are absurdly contradictory." Analyzing technical mediations requires getting out of these false alternatives. In the SSH criticism of data visualization tools, the argument of self-evidence is rarely stated as purely “materialistic” or “sociological”, but it often lacks the details necessary to prevent caricatural interpretations. For instance, Drucker’s statement that “graphical tools are a kind of intellectual Trojan horse” (2011, 2014) may sound absurdly materialistic. Here we apply this model to the case of Gephi, to formalize how practices articulate with its materiality.

Latour offers four meanings for *mediation*: “translation”, “composition”, “reversible blackboxing” and “delegation”. Each meaning corresponds to a certain effect that we can illustrate with Gephi and the argument of self-evidence.

Translation refers to the ability of the user-tool assemblage to displace the goals of both the user and the tool. The goals of researchers using Gephi may differ both from the goals of unequipped researchers and, symmetrically, from the goals of Gephi not in use. Self-evidence may arise without being a goal of Gephi. “Responsibility for action must be shared among the various actants” (Latour, 1994).

Composition refers to the fact that the tool *enables* certain things. Even if we attribute agency to the researcher and not to Gephi, what the equipped researcher can do is rendered possible by both what the researcher can do, and what Gephi can do. Like translation, this meaning of *mediation* emphasizes symmetry between the tool and its user.

Reversible blackboxing refers to the fact that the tool’s transparency is relative and ever-changing. When a device breaks, it has to be unblackboxed to be repaired, and can get blackboxed again to be put in use. Gephi may be more or less blackboxed in different situations, at different moments, or to different people. A researcher may consider Gephi a black box at the moment of using it, as usage requires a form of convergence between the tool and the user, and the same researcher may open the black box at a later moment, when it comes to discuss the method in a publication.

Delegation, the “most important” meaning of mediation according to Latour (1994), and based on the previous three, refers to the ability to shift signification (or more simply, goals). An apparatus may play a rhetorical role, it also has a meaning that is part of no discourse. Technical objects “act, displace goals, and contribute to their redefinition.” Gephi means by enabling researchers to produce visualizations. For instance it may shift their goal from exploring data to producing a network map, simply because it allows them exporting an image.

Gephi’s blackboxing problem derives from its ability to allow users (notably beginners) to produce network maps (without acknowledging methodological norms). Gephi becomes a black box by empowering the user; the problem is with the *delegation* of power inherent to its mediation. Indeed, network maps are an “epistemic surplus” of Gephi, to reuse Rieder and Röhle’s (2017) expression. Gephi can do many things including providing metrics, but it is the ease of producing network maps that shifts user goals. Network maps are valuable assets, and especially within the safe space of the community. Indeed, Gephi’s epistemic culture values network maps even in the absence of methodological background. And symmetrically, Gephi's epistemic culture shifted the goals of the tool, emphasizing its ability to produce images. According to its authors (Bastian *et al.*, 2009), Gephi was designed as a tool for "exploring and manipulating networks," dedicated to "network analysis." The paper highlights a list of features indicating its goals: "spatializing, filtering, navigating, manipulating and clustering." The initial focus of Gephi was on exploration rather than exporting network maps, but its epistemic culture shifted its goal in unexpected ways. The practices around Gephi drifted from analyzing networks towards showcasing them.

We propose, as an emblematic misuse of Gephi, the following scenario, reconstructed after our observations. A well-meaning and rigorous researcher conducts a network exploration with Gephi, and exports a few images to document the process. Engaging with the data through Gephi, a specific topological feature is discovered. The researcher can provide evidence via a statistical metric, but is also capable of recognizing a visual pattern in the images. When it comes to publicizing the finding, in addition or instead of grounding it on a metric, the researcher argues or suggests that *the finding is visible in the picture*. This might be received positively among Gephi enthusiasts, who might also see a pattern. Yet this self-evidence is a misunderstanding. We presume here an honest mistake: the researcher overlooks how much context is required to interpret the image properly, because their own engagement with data has normalized it. In this scenario, self-evidence is not the intentional product of a misleading rhetoric, but a side-effect of the ease of exporting network maps in Gephi. The instrument shifted the goals of its user by offering a valuable by-product, the graphical export, that comes with its own affordances and epistemological commitments.

Conclusion

We have seen that SSH scholars criticize data visualization in general, and network visualization in particular, including Gephi, for being a "black box". This argument blames network maps for appearing self-evident, which leads to forgetting that they come with methodological commitments. By analyzing empirical material from participant observation, interviews, and a publication review, we have diagnosed Gephi's blackboxing problem. We found that not all Gephi users see it as a black box, but beginners are prone to producing unquestioned visualizations. We argued that although Gephi's materiality tends to alleviate blackboxing, it still blackboxes by empowering users to produce network maps even when they do not understand them. We argued that a specific epistemic culture emerged around Gephi, where the circulation of unquestioned network maps is valued. We formalized Gephi's blackboxing problem as an interaction between the instrument and its culture, where Gephi shifts the goals of its users, and symmetrically, the users shift the goals of the tool. Self-evidence arises when Gephi produces an epistemic surplus: easy-to-produce network maps perceived by users as a valuable asset to circulate regardless of its scientific validity.

We initially wondered how to fix Gephi's blackboxing problem. Our findings suggest that intervening on the artifacts of Gephi's subculture (e.g. popular tutorials) might be more efficient than intervening on the tool's software and design. Indeed, although the problem is material-semiotic, it derives from a feature that empowers users, the ease of producing network maps. This feature is useful to advanced users even though it offers a dangerous temptation to beginners, and removing it would harm the instrument. We believe that Gephi's community should give less importance to unquestioned visualizations, and refrain from presenting Gephi to beginners as a tool primarily aimed at exporting visualizations. As we have seen, the graphical dimension of Gephi was primarily intended for exploring the data. Gephi's mode of visualization was firstly intended for the user itself, and only secondarily to share with others. We suggest that network maps are generally much less useful, as a way to provide evidence, than many statistical metrics that Gephi also provide. Future works on that topic might investigate whether social media shaped network practices the same way they shaped cooking, by valorizing good-looking dishes to the detriment of tasty ones. In the meanwhile, we propose that the Gephi community could improve network practices by focusing more on the methodological tenets of network visualization (for such an attempt, see Grandjean and Jacomy, 2019), for example through videos on the exploration process, rather than attractive pictures that cannot be interpreted in a scientific setting.

References

Adamic, L. A., and Glance, N. (2005) The political blogosphere and the 2004 US election: divided they blog, *Proceedings of the 3rd international workshop on Link discovery*, pp. 36-43.

Agre, P. E. (1997) Toward a Critical Technical Practice: Lessons Learned in Trying to Reform AI, In G. C. Bowker, et al. (eds), *Social Science, Technical Systems, and Cooperative Work: Beyond the Great Divide* (Mahwah, NJ: Lawrence Erlbaum Associates), pp. 131–57.

Akrich, M. (1993) *Les formes de la médiation technique*, Réseaux, 60, pp. 87-98.

Barabási, A. L. (2016) *Network science*. (Cambridge: Cambridge university press).

Barnes, J. A. and Harary, F. (1983) *Graph theory in network analysis*, Social Networks, 5, pp. 235-244

Barnett, G. A. and Benefield, G. A. (2017) *Predicting international Facebook ties through cultural homophily and other factors*, New Media & Society, 19(2), 217-239.

Bastian, M., Heymann, S. and Jacomy, M. (2009) *Gephi: an open source software for exploring and manipulating networks*, Third international AAAI conference on weblogs and social media.

Berry, D. M. (2011) *The computational turn: Thinking about the digital humanities*. Culture Machine, 12.

Blondel, V. D., Guillaume, J. L., Lambiotte, R. and Lefebvre, E. (2008) *Fast unfolding of communities in large networks*, Journal of statistical mechanics: theory and experiment, 10.

Bonini, T., Caliandro, A. and Massarelli, A. (2016) *Understanding the value of networked publics in radio: employing digital methods and social network analysis to understand the Twitter publics of two Italian national radio stations*, Information, Communication & Society, 19(1), pp. 40-58.

Borgatti, S. P., Everett, M. G. and Freeman, L. C. (2002) *Ucinet for Windows: Software for social network analysis* (Harvard, MA: Analytic technologies)

Borgatti, S. P., Mehra, A., Brass, D. J. and Labianca, G. (2009) *Network analysis in the social sciences*, Science, 323(5916), pp. 892-895.

Börner, K., Sanyal, S. and Vespignani, A. (2007) *Network science*, Annual review of information science and technology, 41(1), pp. 537-607.

Boyd, D. and Crawford, K. (2012) *Critical questions for big data: Provocations for a cultural, technological, and scholarly phenomenon*, Information Communication and Society, 15(5), pp. 662–679. https://doi.org/10.1080/1369118X.2012.678878

Bruns, A. (2013) *Faster than the speed of print: Reconciling 'big data' social media analysis and academic scholarship*, First Monday, 18(10). http://firstmonday.org/ojs/index.php/fm/article/view/4879

Bruns, A., Moon, B., Münch, F. and Sadkowsky, T. (2017) *The Australian Twittersphere in 2016: Mapping the follower/followee network*. Social Media + Society, 3(4), 2056305117748162.

Butts, C. T. (2009) *Revisiting the foundations of network analysis*. Science, 325(5939), pp. 414-416.

Celli, F. and Rossi, L. (2012) *The role of emotional stability in Twitter conversations.*, Proceedings of the workshop on semantic analysis in social media, pp. 10-17. Association for Computational Linguistics.

Chiesi, A. M. (2015) *Network Analysis*, International Encyclopedia of the Social & Behavioral Sciences, pp. 518–523. https://doi.org/10.1016/B978-0-08-097086-8.73055-8

Diminescu, D. (2012) *Diasporas on the Web*, Social science information, 51(4).

Diminescu, D., Bourgeois, M., Renault, M. and Jacomy, M. (2011) *Digital Diasporas Atlas Exploration and Cartography of Diasporas in Digital Networks*, Fifth International AAAI Conference on Weblogs and Social Media, pp. 657–658.

Diminescu, D., Asal, H., Balalovska, K., Ben-David, A., Berthomière, W., Bruslé, T., Carsignol, A., Gangloff, S., Graziano, T., Knaute, D., Kumar, P., Le Bayon, S., Leclerc, É., Ma Mung Kuang, E., Marchandise, S., Mazzucchelli, F., Morgunova (Petrunko), O., Moua, M. H., Percot, M., Renault, M., Reyhan, D., Scioldo Zürcher, Y., Severo, M., Therwath, I., Varrel, A., Venier, P., Watin, M., Wolff, E. and Zuolo, E. (2012) *e-Diasporas Atlas*. Available at http://www.e-diasporas.fr (accessed 18 August 2020).

Dunne, C., Ross, S. I., Shneiderman, B. and Martino, M. (2015) *Readability metric feedback for aiding node-link visualization designers*, IBM Journal of Research and Development, 59(2/3), pp. 11–14. https://doi.org/10.1147/JRD.2015.2411412

Drucker, J. (2011) *Humanities approaches to graphical display*, Digital Humanities Quarterly, 5(1), pp. 1-21.

Drucker, J. (2012) Humanistic Theory and Digital Scholarship, In: Matthew K. Gold (Ed.) *Debates in the Digital Humanities* (Minneapolis: University of Minnesota Press), pp. 85-95.

Drucker, J. (2013) *Performative Materiality and Theoretical Approaches to Interface*, DHQ: Digital Humanities Quarterly, 7(1).

Drucker, J. (2014) *Graphesis: Visual Forms of Knowledge Production* (Cambridge, MA: Harvard University Press).

Erdős, P. and Rényi, A. (1960) *On the evolution of random graphs*. Publ. Math. Inst. Hung. Acad. Sci, 5(1), pp. 17-60.

Erikson, E. (2013) *Formalist and relationalist theory in social network analysis*, Sociological Theory, 31(3), pp. 219–242. https://doi.org/10.1177/0735275113501998

Foucault Welles, B. and Meirelles, I. (2014) *Visualizing Computational Social Science: The Multiple Lives of a Complex Image*, Science Communication, pp. 1–25. https://doi.org/10.1177/1075547014556540

Freeman, L. (2004) *The development of social network analysis*, A Study in the Sociology of Science, 1, 687.

Gibson, H., Faith, J. and Vickers, P. (2012) *A survey of two-dimensional graph layout techniques for information visualisation*, Information Visualization, 12(3–4), pp. 324–357. https://doi.org/10.1177/1473871612455749

Grandjean, M. and Jacomy, M. (2019) *Translating Networks: Assessing Correspondence Between Network Visualisation and Analytics*, Digital Humanities Conference. Available at https://halshs.archives-ouvertes.fr/halshs-02179024 (accessed 2020-09-17)

Grundberg, M. D. and Lindgren, S. (2015) *Translocal frame extensions in a networked protest: Situating the #IdleNoMore hashtag*, IC Revista Científica de Información y Comunicación, (11).

Hagen, L., Keller, T., Neely, S., DePaula, N. and Robert-Cooperman, C. (2018) *Crisis communications in the age of social media: A network analysis of Zika-related tweets*, Social Science Computer Review, 36(5), pp. 523-541.

Haraway, D. (1988) *Situated knowledges: The science question in feminism and the privilege of partial perspective*, Feminist studies, 14(3), pp. 575-599.

Hemsley, B. and Palmer, S. R. (2016). *Two Studies on Twitter Networks and Tweet Content in Relation to Amyotrophic Lateral Sclerosis (ALS): Conversation, Information, and 'Diary of a Daily Life'*, Studies in health technology and informatics, pp. 41-47.

Herdağdelen, A., State, B., Adamic, L. and Mason, W. (2016) *The social ties of immigrant communities in the United States*, Proceedings of the 8th ACM Conference on Web Science, pp. 78-84.

Hidalgo, C. A. (2016) *Disconnected, fragmented, or united? a trans-disciplinary review of network science*, Applied Network Science, 1(1), pp. 1–19. https://doi.org/10.1007/s41109-016-0010-3

Jacomy, M., Venturini, T., Heymann, S., & Bastian, M. (2014). ForceAtlas2, a continuous graph layout algorithm for handy network visualization designed for the Gephi software. PloS one, 9(6).

Johnson, J. C. and Weller, S. C. (2002) Elicitation techniques for interviewing, In: Gubrium J. F. and Holstein J. A. (Eds.) *Handbook of interview research: Context and method* (Thousands Oaks, CA: SAGE Publications), pp. 491-514.

Jokubauskaite, E. (2018) *Gephi and its Context: Three Oppositions in The Epistemic Culture of Network Analysis And Visualisation* (Amsterdam: University of Amsterdam).

Knoke, D. and Yang, S. (2019) *Social network analysis* (Thousands Oaks, CA: SAGE Publications).

Knorr Cetina, K. D. (1999) *Epistemic cultures: How the sciences make knowledge* (Cambridge, MA: Harvard University Press).

Knorr Cetina, K. and Reichmann, W. (2015) *Epistemic Cultures*, International Encyclopedia of the Social & Behavioral Sciences: Second Edition (Amsterdam: Elsevier), pp. 873–880. https://doi.org/10.1016/B978-0-08-097086-8.10454-4

Krzywinski, M., Birol, I., Jones, S. J. and Marra, M. A. (2012) *Hive plots—rational approach to visualizing networks*, Briefings in bioinformatics, 13(5), pp. 627-644.

Larsson, A. O. (2013) *Tweeting the viewer—use of Twitter in a talk show context*, Journal of broadcasting & electronic media, 57(2), pp. 135-152.

Larsson, A. O. and Moe, H. (2014) *Triumph of the underdogs? Comparing Twitter use by political actors during two Norwegian election campaigns*. Sage Open, 4(4), 2158244014559015.

Latour, B. (1986) Visualisation and Cognition: Drawing Things Together. In: Kucklick, H. (Ed) *Knowledge and Society Studies in the Sociology of Culture Past and Present* vol. 6 (Greenwich, CT: Jai Press), pp. 1-40.

Latour, B. (1994) *On Technical Mediation*, Common Knowledge, 3(2), pp. 29-64.

Latour, B. (1999) *Pandora's Hope: Essays on the Reality of Science Studies* (Cambridge, MA: Harvard University Press).

Latour, B. (2000) Opening Pandora's Black Box, In: Dawson, P., McLoughlin, I., and Preece, D. (Eds.) *Technology, Organizations and Innovation: Critical Perspectives on Business and Management* (Abingdon: Routledge), pp. 679–698.

Law, J. (2011) Collateral realities. In: Dominguez Rubio, F. and Baert, P. (Eds.) *The Politics of Knowledge* (London: Routledge), pp. 156–178.

Lazer, D., Pentland, A., Adamic, L., Aral, S., Barabási, A. L., Brewer, D., Christakis, N., Contractor, N., Fowler, J., Gutmann, M., Jebara, T., King, G., Macy, M., Roy, D. and Van Alstyne, M. (2009) *Computational social science*, Science, 323(5915), pp. 721-723.

Lemercier, C. and Zalc, C. (2019) *Quantitative Methods in the Humanities: An Introduction*, (Charlottesville: University of Virginia Press).

Lévy-Strauss, C. (1973) *Anthropologie structurale deux* (Paris: Plon), pp. 33-34.

Lindgren, S. (2013) *The potential and limitations of Twitter activism: Mapping the 2011 Libyan Uprising*, tripleC: Communication, Capitalism & Critique. Open Access Journal for a Global Sustainable Information Society, 11(1), pp. 207-220.

Magnani, M., Montesi, D., and Rossi, L. (2010) *Friendfeed breaking news: Death of a public figure*, 2010 IEEE Second International Conference on Social Computing, pp. 528-533. IEEE.

Manovich, L. (2013) *Software Takes Command* (New York: Bloomsbury Academic).

Marres, N. (2012) *On some uses and abuses of topology in the social analysis of technology (or the problem with smart meters)*, Theory, Culture & Society, 29(4-5), pp. 288-310.

Marres, N. (2017). *Digital Sociology* (Cambridge: Polity Press).

Masson, E. (2017) Humanistic Data Research: An Encounter between Epistemic Traditions. In: M. T. Schäfer & K. van Es (Eds.) *The Datafied Society: Studying Culture Through Data* (Amsterdam: Amsterdam University Press), pp. 109–124.

Merleau-Ponty, M. (1962) [1945]. *Phenomenology of Perception*. transl. Colin Smith (New York: Humanities Press).

Metaxas, P. and Mustafaraj, E. (2013) *The rise and the fall of a citizen reporter*, Proceedings of the 5th Annual ACM Web Science Conference, pp. 248-257.

Meyer, E. T. and Schroeder, R. (2015) *Knowledge Machines: Digital Transformations of the Sciences and Humanities* (Cambridge: MIT Press).

Milgram, S. (1967) *The small world problem*, Psychology today, 2(1), pp. 60-67.

Moreno, J. L. (1934) *Who Shall Survive?* (Washington, DC: Nervous and Mental Disease Publishing Company).

Munzner, T. (2015) *Visualization Analysis and Design* (Boca Raton: CRC Press).

Newman, M. (2018) *Networks* (Oxford: Oxford university press).

O'Callaghan, D., Greene, D., Conway, M., Carthy, J. and Cunningham, P. (2013) *Uncovering the wider structure of extreme right communities spanning popular online networks*, Proceedings of the 5th Annual ACM Web Science Conference, pp. 276-285.

Paßmann, J. and Boersma, A. (2017) Unknowing Algorithms: On Transparency of Unopenable Black Boxes, In: Schäfer, M. T. and van Es, K. (Eds.) *The Datafied Society. Studying Culture through Data* (Amsterdam: Amsterdam University Press). https://doi.org/10.5117/9789462981362

Rieder, B. (2013) *Studying Facebook via Data Extraction: The Netvizz Application*, Proceedings of the 5th Annual ACM Web Science Conference (WebSci'13). Pp. 346–355. https://doi.org/10.1145/2464464.2464475

Rieder, B. and Röhle, T. (2012) Digital Methods: Five Challenges. In: Berry, D. M. (Ed.) *Understanding Digital Humanities* (New York: Palgrave Macmillan), pp. 67-8.

Rieder, B. and Röhle, T. (2017) Digital methods: From challenges to Bildung, In: Schäfer, M. T. and van Es, K. (Eds.) *The Datafied Society. Studying Culture through Data* (Amsterdam: Amsterdam University Press), pp. 109-124. https://doi.org/10.5117/9789462981362

Rogers, R. (2013) *Digital methods* (Cambridge: MIT Press).

Ruppert, E., Law, J. and Savage, M. (2013) *Reassembling social science methods: The challenge of digital devices*, Theory, culture & society, 30(4), pp.22-46.

Ruppert, E. and Scheel, S. (2019) *The Politics of Method: Taming the New, Making Data Official*, International Political Sociology, 13(3), pp. 233-252.

Savage, M. and Burrows, R. (2007). *The coming crisis of empirical sociology*, Sociology, 41(5), pp. 885–899.

Simondon, G. (1958) *Du mode d'existence des objets techniques* (Paris: Aubier).

Star, S. L., Bowker, G. C. and Neumann, L. J. (2003) Transparency beyond the Individual Level of Scale: Convergence between Information Artifacts and Communities of Practice, In: Peterson-Kemp, A., Van House, N. A. and Buttenfield, B. P. (Eds.) *Digital Library Use* (Cambridge: MIT Press), pp. 241–269. https://doi.org/10.7551/mitpress/2424.003.0014

Tukey, J. W. (1977) *Exploratory Data Analysis* (Reading, MA: Addison-Wesley).

van Es, K., Wieringa, M. and Tobias Schäfer, M. (2018) *Tool Criticism: From Digital Methods to Digital Methodology*, Proceedings of the 2nd International Conference on Web Studies. https://doi.org/10.1145/3240431.3240436

van Es, K. and Schäfer, M. T. (2017). *The datafied society. Studying culture through data* (Amsterdam: Amsterdam University Press), Section 2, pp. 109-182.

van Geenen, D. and Wieringa, M. (2020) *Approaching data visualizations as interfaces: An empirical demonstration of how data are imag(in)ed*, Data Visualization in Society, 141.

Veltri, G. A. and Atanasova, D. (2017) *Climate change on Twitter: Content, media ecology and information sharing behaviour*, Public Understanding of Science, 26(6), pp. 721-737.

Venturini, T., Jacomy, M. and Jensen, P. (2019) *What do we see when we look at networks?* arXiv preprint arXiv:1905.02202 (accessed 2020-09-17).

Venturini, T., Jacomy, M. and Pereira, D. (2014) *Visual network analysis*. Available at: https://pdfs.semanticscholar.org/67e4/8238146119ea4081da4f3f0d0dc3aa1cb4b6.pdf (accessed 2020-09-17)

White, H. (1963) *An Anatomy of Kinship: Mathematical Models for Structures of Cumulated Roles* (Engelwood, NJ: Prentice Hall).

Wieringa, M., Geenen, D., van Es, K. and van Nuss., J. (2019) The Field Notes Plugin: Making Network Visualization in Gephi Accountable, In: Daly, A., Devitt, K. and Mann., M. (Eds) *Good Data. INC Theory on Demand*. Available at http://networkcultures.org/blog/publication/tod-29-good-data/ (accessed 2020-09-17)

[i] As per Wikipedia (accessed 2020-08-11), Bildung "refers to the German tradition of self-cultivation … , wherein philosophy and education are linked in a manner that refers to a process of both personal and cultural maturation."
[ii] According to Google Scholar at the time of writing (June 2020)
[iii] https://www.facebook.com/groups/gephi/ All the URLs featured in footnotes have been last checked on 18 August 2020.
[iv] Available online: https://quanthum.hypotheses.org/176
[v] https://www.facebook.com/groups/gephi/
[vi] See for instance:
http://www.martingrandjean.ch/gephi-introduction/
https://www.pauloldham.net/gephi_patent_network/
[vii] https://gephi.org/
[viii] https://github.com/gephi/gephi/wiki
[ix] *Mastering Gephi Network Visualization* and *Network Graph Analysis and Visualization with Gephi*, by Ken Cherven; and *Gephi Cookbook*, by Devangana Khokhar; all three edited by Packt.
[x] https://wiki.digitalmethods.net/
[xi] 1255 according to Google Scholar, June 2020

APPENDIX G. EPISTEMIC CLASHES IN NETWORK SCIENCE

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Epistemic clashes in network science: Mapping the tensions between idiographic and nomothetic subcultures

Mathieu Jacomy

Abstract
This article maps a controversy in network science over the last 15 years, dividing the field about the epistemic status of a central notion, scale-freeness. The article accounts for the two main disputes, in 2005 and in 2018, as they unfolded in academic publications and on social media. This article analyzes the conflict, and the reasons why it reignited in 2018, to the surprise of many. It is argued that (1) the concept of complex networks is shared by the distinct subcultures of theorists and experimentalists; and that (2) these subcultures have incompatible approaches to knowledge: *nomothetic* (scale-freeness is the sign of a universal law) and *idiographic* (scale-freeness is an empirical characterization). Following Galison, this article contends that network science is a *trading zone* where theorists and experimentalists can trade knowledge across the epistemic divide.

Keywords
Complex network, controversy mapping, network practices, network science, nomothetic and idiographic, scale-freeness

> [S]cience is disunified, and – against our first intuitions – it is precisely the disunification of science that underpins its strength and stability. (Galison, 1999: 137)

Readers from the field of Science and Technology Studies (STS) have encountered the network, and likely observed how disunified it can be: following Galison's (1999: 157) metaphor, a laminated mess of "partially independent strata supporting one another". As we argued in a previous article (Venturini et al., 2019), STS engage with the network in multiple ways. Actor-network theory (ANT) used the network as a metaphor to criticize "notions as diverse as institution, society, [and] nation-state" (Latour, 1999: 15; see also Law, 1999), although post-ANT moved away from networks. More recently, at the intersection of digital media studies and STS, some scholars use the network as a "social science apparatus" (Ruppert et al., 2013), often in a perspective of critical proximity, while reflecting on the network's pervasive involvement in the infrastructure of datafied society. In this context, like other forms of Big Data, the network's material-semiotic properties produce data-worlds, for instance, as network maps are interpreted as if they are self-evident (Bounegru et al., 2017; Burrows and Savage, 2014; Marres and Gerlitz, 2016). This movement is critical of Computational Social Science (Lazer et al., 2009), and concerned with the theories and models embodied in network tools (Rieder and Röhle, 2017), and their uses and abuses (Marres, 2012). STS scholars know how problematic the network can be, as the confusion it causes has been documented. Nevertheless, they did not create their own trouble with networks (van Geenen et al., forthcoming); they imported it.

STS scholars tend to presume that the disunification of the network happened when it was repurposed from the exact sciences, where the network was originally unified. But this initial state of unity never existed: The network has always been disputed.

There is no doubt that the *raison d'être* of the network is that relations deserve no less attention than

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substance; but even that point takes incompatible meanings in different contexts. Latour (2004: 63) warns STS scholars: "you should not confuse the network that is drawn by the description and the network that is used to make the description. . . . Surely you'd agree that drawing with a pencil is not the same thing as drawing the shape of a pencil. It's the same with this ambiguous word, network." The network can be either something we can know or a way to know things (this argument is developed in Venturini et al., 2019).

In sociology, Erikson (2013) accounts for a slightly different opposition, between the *relationalist* approach, which "rejects [the] essentialism" of the network, and the *formalist* approach based on a "structuralist interpretation". Even within the formalist approach, prevalent in the natural sciences, the network has conflicting significations.

The transdisciplinary field network science (NS) emerged in the late 1990s under the joint patronage of social network analysis and the study of complex systems (Barabási, 2016; Borgatti et al., 2009), focusing on a specific type of network: the *complex network*. From this crucible dominated by the formalist influence of physicists, statisticians, and quantitative sociologists (Hidalgo, 2016), old and new theories and methods radiate toward the social and natural sciences (Freeman, 2008; Newman, 2018). Despite its success, NS witnesses a "clash of two cultures" (Keller, 2007) where fundamental claims on *scale-freeness* are disputed for more than a decade.

In this piece, I follow in the footsteps of Galison (1999) in *Trading Zones*, but focus on NS. Like him, I account for the frictions and exchanges between different subcultures. I find experimentalists whose ways and goals challenge those of theorists. I find that the (complex) network is a shared object that gets attributed different meanings in different contexts while allowing knowledge to circulate over epistemic gaps, and allowing the field to maintain its continuity. I argue that controversies in NS illustrate a familiar tension between digital methods and computational social science (Baya-Laffite and Benbouzid, 2017; Masson, 2017), and I show that it extends the gap present in the exact sciences: the nomothetic/idiographic divide.

After introducing the key concepts of NS, and then my method, I account for the first dispute, in 2005, regarding which statistical distributions characterize complex networks. I analyze its commonly accepted framing as a tension between disciplines, and I explain why the subsequent efforts of multiple authors to defend a position of compromise did not put an end to the controversy. Then I introduce the notions of nomothetic and idiographic approaches to knowledge, and account for the second dispute, in 2018, concerning the experimental procedures capable of assessing the (alleged) pervasiveness of complex networks. Finally, I reframe the second dispute as an epistemic clash between theorists and experimentalists, the latter gradually opposing their own agenda to the former.

Network science is a controversial field

NS is not a firmly delineated discipline but a "highly interdisciplinary research area" (Börner et al., 2007) whose origin is disputed. For Borgatti et al. (2009), NS emanates from the older and well-established field of *social network analysis*. For Barabási (2016) and Hidalgo (2016), NS's roots are in the study of complex systems in the natural sciences, and for Brandes et al. (2013), in a transdisciplinary mathematical apparatus.

Despite these different perspectives, all scholars acknowledge multiple points of origin, and the trouble it causes. Freeman (2008) accounts for two distinct communities within the field, and their mutual influence. Keller (2005, 2007) argues against the "lure of universality" and points to a "clash of two cultures". Erikson (2013: 219) writes that the field "often mixes two distinct theoretical frameworks, creating a logically inconsistent foundation." Hidalgo (2016) wonders whether the field is "disconnected, fragmented, or united," arguing that social and natural scientists do not understand each other because they have different goals. However, although there is consensus on the presence of tensions between disciplines, these authors disagree about which disciplines are clashing, and why.

I argue that the hypothesis of a disciplinary divide is not sufficient, as it fails to explain why the controversy reignites in 2018—which network scientists see as "surprising" (Holme, 2019). Before we get to that point, I must briefly present NS and several concepts necessary for understanding its contentious points.

The key concepts of network science

NS focuses on the study of complex networks. Euler's work in the 18th century gives birth to graph theory, and Moreno's (1934) *sociograms* initiate the practice of visualizing social networks (Freeman, 2000). During the late 1990s, NS emerges as an interdisciplinary field around the object *complex network* (Barabási, 2016; Borgatti et al., 2009; Börner et al., 2007). The notion is invented almost simultaneously by two different teams: Watts and Strogatz (1998), who call it *small-world* and Barabási and Albert (1999), who call it *scale-free*. Both teams draw inspiration from the work of Erdős and Rényi (1960) on the *random graph model*, a probabilistic version of the network. It matches for the first time general properties of many empirical phenomena (see Barabási, 2002). The **complex network** has no precise definition, but nevertheless, refers to a special kind, as Wikipedia puts it, one "with non-trivial topological features". In a nutshell, complex networks stand somewhere between order and disorder (see Figure 1).

The NS controversy is specifically about **scale-freeness**, a criterion Barabási and Albert use to characterize complex networks. In their model, as a network grows, its new nodes favor linking to the most connected nodes, a phenomenon known as **preferential attachment**. This phenomenon is similar to the Matthew effect (Merton, 1968), also known as "the rich get richer, and the poor get poorer." The resulting network is called "scale-free" because it features the same properties across multiple scales. Specifically, the **degree** of the nodes, i.e., the number of neighbors, follows a **power-law distribution** (a statistical distribution itself scale-free). In practical terms, a few nodes get the most links (the "hubs"), while most nodes are poorly connected.

Pervasiveness is not a concept of NS, but a term I use to refer to one of its main rhetorical points: the empirical observation of the same phenomenon across many *unrelated* situations. Pervasiveness calls for an answer to an implicit question: Why do we observe the same thing in contexts that have *a priori* nothing in common? If your goal is to discover laws of nature, pervasiveness is a remarkable observation, because it suggests an underlying pattern.

Universality is a misleading but important concept, which one needs to understand at least superficially. The pervasiveness of the power law has been known in thermodynamics since the 1970s, under the pompous name of universality (Feigenbaum, 1976). Physicists explain this pervasiveness with the concept of self-organized criticality (Bak et al., 1987), which states that the power law naturally arises at the tipping point of a phase transition (called "criticality") for mathematical reasons related to scale-freeness. Physicists such as Barabási translate this argument from thermodynamics to NS, based on three facts. (1) Phase transition and the Erdős–Renyi random graph model are instances of a process known as **percolation** (the emergence of a "strongly connected component" in a random graph is similar to the apparition of ice crystals in cooling water). (2) The power law and the complex network are pervasive. (3) The power law characterizes complex networks (via scale-freeness). From these premises, physicists deduce that the power law is the external sign of an underlying complex network. This idea took the name of universality because it extends Feigenbaum's work, but it actually means something quite different. Feigenbaum's universality is only an observation; NS's universality states a law of nature.

I refer to this as the *argument of universality*, and the important point is to track how it changes. The argument appears under different forms in the publications of network scientists such as Barabási. In its strongest form, it affirms the *existence of a universal law* of complexity, explaining the pervasiveness of the power law and the complex network. The claim is supposed to be rooted in a mixture of graph theory and physics of complex systems, but experimental results gradually accumulated as evidence against it. The claim then degrades into a weaker form, stating the existence of *unspecified laws*, on the grounds of the pervasiveness of the properties of the complex network. Finally, in its weakest form, universality means only *pervasiveness*, which fits its colloquial meaning and Feigenbaum's version. The strongest form claims the existence of a law; the weakest is only an empirical observation. The weak version requires only evidence, but the strong version also requires a theory. These different meanings must not be conflated because they have different validity conditions. Some researchers voice this criticism (Watts and Clauset as cited in Klarreich, 2018). As Barrat et al. (2008: 296) put it, "physicists know extremely well that the universality of some statistical laws is not to be confused with the 'equivalence

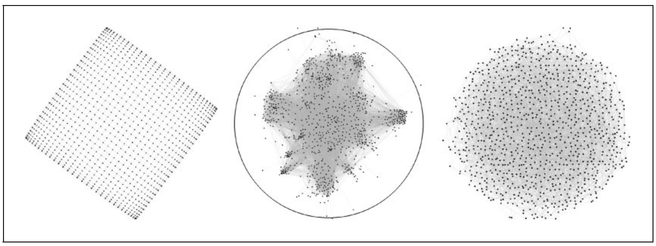

Figure 1. Three types of networks, about 1000 nodes each. The complex network (center) is sometimes presented as an intermediary between order (left, a square lattice) and disorder (right, a random network).

of systems'." In the current state of the controversy, even the weakest form is contested.

Many researchers challenge the pervasiveness of the power law based on its resemblance to the **log-normal** distribution (a cousin of the famous *normal distribution*, aka the "bell curve"). Both are quite similar in practice, when it comes to matching empirical observations, but scale-freeness is related only to the power law, via the preferential attachment model. In this dispute, the empirical ground of scale-free pervasiveness is at stake. The **heavy-tailed distribution** is a notion introduced subsequently to subsume the log-normal and power-law distributions.

Mapping the controversy

The controversy unfolds in two distinct moments, characterized by the accumulation of traces in the digital public space as network scientists debate on their blogs, Twitter, and arXiv, a platform hosting non-peer-reviewed pre-prints. The first dispute happens in 2005 and focuses on the resemblance between the log-normal and power-law distributions. The second happens in 2018 and challenges more directly the measure of scale-freeness.

My methodology is based on document analysis and draws on controversy mapping (Venturini, 2010). I "follow the actors" (Latour, 1987) to identify the points they see as controversial. I often refer to the researchers involved in the debates as *actors* or *network scientists*, for simplicity and because they all engage with NS, although they do not always qualify themselves as such.

The controversy has no clear boundaries. The NS concepts and methods are challenged and discussed over its two decades of existence, as for any scientific field. In this article, I specifically investigate the contentious points whose resolution is contested by actors: when they also disagree about their disagreement.

I coded a selection of 40 academic and non-academic publications related to the controversy. I explored the literature with snowballing sampling before reducing the corpus to a set of key documents. I selected explicit refutations, refuted articles, commentary, major publications citing the disputes (e.g., attempts at concluding them), and major references. See Table 1 for the list and Figure 3 for a contextualized visualization.

Figures 2 and 3 help familiarize readers with the corpus. For the sake of clarity, I classified the documents into four groups. The initial references in 1999–2000 show early signs of the controversy. I gathered publications explicitly referring to each academic feud in the 2005 dispute and the 2018 dispute. The ongoing discussion group contains contributions that do not refer explicitly to either feud.

The evolution of citations (Figure 2) shows that the 2005 controversy is rarely cited by subsequent publications. The 2018 controversy largely builds on the 2007–2016 academic discussion.

Placing the documents and their type in chronological order (Figure 3) shows that two waves of reactions happen after the publication of a polemic piece: self-published web commentary in the following weeks and then, academic articles featuring refutations in the following years.

I reduced my qualitative exploration of this corpus to a coding of 12 different arguments framing the controversy, expressing a specific perspective on scale-freeness and universality, or taking an epistemic posture. Each of the 120 data points consists of a brief quote exemplifying a given argument featured in a given publication. The data is available as supplemental material.

I further reduced this corpus by focusing on the 13 most recurrent actors: Alderson, Doyle, and Willinger (who always published together in this corpus), Amaral and Malmgren (idem), Barabási, Barzel, Clauset, Holme, Mitzenmacher, Shalizi, Vespignani, and Watts. Figure 4 shows the co-publication groups in the corpus. These 13 key actors effectively form 10 groups or single actors. I picked this number to ensure that each presented enough material for the analysis.

I compiled the statements of the key actors by period in a table available as supplemental material. It comprises 79 quotes. Table 2 presents each argument with two examples of quotes. Figure 5 features which key actor states which argument during which period.

Actors' view of the controversy

Before engaging with the matter of the two disputes, I summarize how the actors of the controversy frame it themselves. Their recurrent arguments are the following:

1. A disciplinary divide
2. A matter of how public relations are enacted by certain researchers
3. An issue of conceptual ambiguity

Argument 1

"For Vespignani, the debate illustrates a gulf between the mindsets of physicists and statisticians" (Klarreich, 2018). A similar opinion is voiced by half of the key actors (see Figure 4), although the problem is rarely situated precisely. Holme (2018b) characterizes the

Table 1. Corpus of documents coded for this study, chronological order.

Reference	Title	Publication date	Type of document	Person(s) expressing views (key actors in bold)
Albert et al. (1999)	Diameter of the world-wide web	09 Sep 1999	Peer-reviewed publication	Albert; Jeong; **Barabási**
Barabási and Albert (1999)	Emergence of scaling in random networks	15 Oct 1999	Peer-reviewed publication	Barabási; Albert
Adamic and Huberman (2000)	Power-law distribution of the world wide web	24 Mar 2000	Peer-reviewed publication	Adamic; Huberman
Barabási et al. (2000)	Response to power-law distribution of the world wide web	24 Mar 2000	Peer-reviewed publication	Barabási; Albert; Jeong; Bianconi
Mitzenmacher (2004)	A brief history of generative models for power law and lognormal distributions	01 Jan 2004	Peer-reviewed publication	**Mitzenmacher**
Willinger et al. (2004)	More "normal" than normal: Scaling distributions and complex systems	05 Dec 2004	Peer-reviewed publication	Willinger; **Alderson**; **Doyle**; Li
Barabási (2005)	The origin of bursts and heavy tails in human dynamics.	12 May 2005	Peer-reviewed publication	**Barabási**
Doyle et al. (2005)	The "robust yet fragile" nature of the Internet	11 Oct 2005	Peer-reviewed publication	Doyle; **Alderson**; Li; Low; Roughan; Shalunov; Tanaka; **Willinger**
Stouffer et al. (2005)	Comment on Barabasi (2005)	25 Oct 2005	Online pre-print	Stouffer; **Malmgren**; **Amaral**
Clauset (2005a)	Links, links, links	27 Oct 2005	Self-published online post	**Clauset**
Keller (2005)	Revisiting "scale-free" networks	27 Oct 2005	Peer-reviewed publication	Keller
Shalizi (2005)	Gauss is not mocked	28 Oct 2005	Self-published online post	**Shalizi**
Venkatasubramanian (2005)	Darwin's and Einstein's (e)mail correspondence rates, or a rumination on power laws	28 Oct 2005	Self-published online post	Venkatasubramanian
Venkatasubramanian (2005)	Darwin's and Einstein's (e)mail correspondence rates, or a rumination on power laws	28 Oct 2005	Self-published online post	***Mitzenmacher***
Raza (2005)	Power law vs. log-normal distributions	02 Nov 2005	Self-published online post	Raza
Barabási et al. (2005)	Reply to comment on "The origin of bursts and heavy tails in human dynamics"	22 Nov 2005	Online pre-print	Barabási; Goh; Vazquez
Clauset (2005b)	Irrational exuberance plus indelible sniping yields delectable entertainment	27 Nov 2005	Self-published online post	**Clauset**
Stouffer et al. (2006)	Log-normal statistics in e-mail communication patterns	03 May 2006	Online pre-print	Stouffer; **Malmgren**; **Amaral**
Keller (2007)	A clash of two cultures	07 Feb 2007	Peer-reviewed publication	Keller
Barrat et al. (2008)	Dynamical processes on complex networks	01 Sep 2008	Book	Barrat; Barthelemy; **Vespignani**
Malmgren et al. (2008)	A Poissonian explanation for heavy tails in e-mail communication	25 Nov 2008	Peer-reviewed publication	Malmgren; Hofman; **Amaral**; **Watts**
Clauset et al. (2009)	Power-law distributions in empirical data	09 Feb 2009	Peer-reviewed publication	Clauset; **Shalizi**; Newman
Willinger et al. (2009)	Mathematics and the internet: A source of enormous confusion and great potential	01 May 2009	Peer-reviewed publication	**Willinger**; **Alderson**; **Doyle**
Malmgren et al. (2009)	Characterizing individual communication patterns	28 Jun 2009	Peer-reviewed publication	Malmgren; Hofman; **Amaral**; **Watts**

(continued)

Table 1. Continued

Reference	Title	Publication date	Type of document	Person(s) expressing views (key actors in bold)
Shalizi (2010)	So, you think you have a power law, do you? well isn't that special?	18 Oct 2010	Presentation slides	**Shalizi**
Stumpf and Porter (2012)	Critical truths about power laws	10 Feb 2012	Peer-reviewed publication	Stumpf; Porter
Muchnik et al. (2013)	Origins of power-law degree distribution in the heterogeneity of human activity in social networks	07 May 2013	Peer-reviewed publication	Muchnik; Pei; Parra; Reis; Andrade; Havlin; Makse
Barzel and Barabási (2013)	Universality in network dynamics	08 Sep 2013	Peer-reviewed publication	**Barzel**; **Barabási**
Pachter (2014)	The network nonsense of Albert-László Barabási	10 Feb 2014	Self-published online post	Pachter
Perc (2014)	The Matthew effect in empirical data	01 Sep 2014	Peer-reviewed publication	Perc
Barabási (2016)	Network Science	01 Jan 2016	Book	**Barabási**
Broido and Clauset (2018)	Scale-free networks are rare	09 Jan 2018	Online pre-print	Broido; **Clauset**
Holme (2018a)	Power-laws and me	12 Jan 2018	Self-published online post	**Holme**
Barzel (2018)	Spherical cows are rare	18 Jan 2018	Self-published online post	**Barzel**
Klarreich (2018)	Scant evidence of power laws found in real-world networks	15 Feb 2018	Magazine article	Klarreich
Klarreich (2018)	Scant evidence of power laws found in real-world networks	15 Feb 2018	Magazine article	***Vespignani***
Klarreich (2018)	Scant evidence of power laws found in real-world networks	15 Feb 2018	Magazine article	***Watts***
Klarreich (2018)	Scant evidence of power laws found in real-world networks	15 Feb 2018	Magazine article	***Clauset***
Barabási (2018)	Love is all you need: Clauset's fruitless search for scale-free networks	06 Mar 2018	Self-published online post	**Barabási**
Holme (2018b)	Steak-pun networks: The state of affairs	08 Nov 2018	Self-published online post	**Holme**
Zenil (2018)	Response to: As a network scientist, what are your reactions to the 'Scale-free networks are rare' paper by Broido and Clauset?	01 Dec 2018	Self-published online post	Zenil
Broido and Clauset (2019)	Scale-free networks are rare	04 Mar 2019	Peer-reviewed publication	Broido; **Clauset**
Holme (2019)	Rare and everywhere: Perspectives on scale-free networks	04 Mar 2019	Peer-reviewed publication	**Holme**
Alderson et al. (2019)	Lessons from "A first-principles approach to understanding the Internet's router-level topology."	19 Aug 2019	Online pre-print	**Alderson**; **Doyle**; **Willinger**

Lines in italic indicate views expressed by actors other than the authors of the document (quotes). Data available as supplemental material.

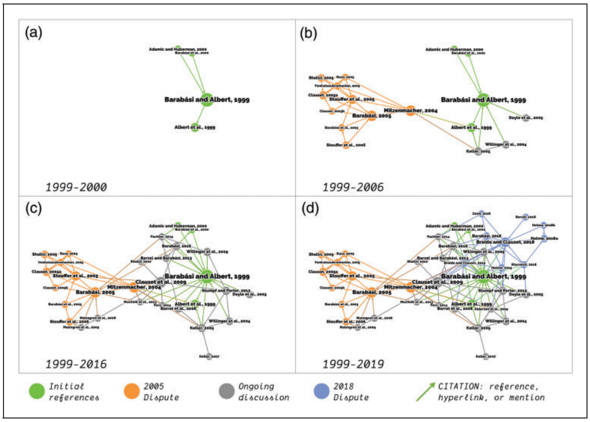

Figure 2. Network of citations between coded publications over time. The node size indicates the number of times cited in the corpus.

divide as "emergentists" who "didn't lose faith in the buzzwords of the nineties' complexity science" such as "universality" versus "statisticalists" for whom "scale-freeness is not scientifically important if it is not testable." Keller (2007) similarly points at the goal of seeking laws of nature: "biologists have been little concerned about whether their findings might achieve the status of a law. . . . Physical scientists, however, come from a different tradition—one in which the search for universal laws has taken high priority." However, in contrast to the hypothesis of a disciplinary divide, Clauset insists instead on the "importance of . . . good statistics" regardless of the discipline (Keller, 2005).

Argument 2

Barabási's critiques condemn his "grand claims of universality" and his "apparent arrogance" (Clauset, 2005b). The former symmetrically suggests that the latter exaggerate their claims "to get maximal attention" (Barabási, 2018). Barabási's fiercest opponents see a scientific issue in his promotion of what they consider disproved claims: "Garbage In, Gospel Out" (Willinger et al., 2009: 598). However, Barabási always responds to the refutation of his articles (see the red arrows in Figure 3) and is supported by respected researchers (Holme, 2019). There is no consensus on the disproval of Barabási's claims, and some even find that "all his talk about networks is good for computer science in general" (Venkatasubramanian, 2005).

Argument 3

In 2018, Clauset and Holme mention conceptual ambiguity as a cause of the controversy. More generally, many authors acknowledge the absence of a clear definition for important concepts, occasionally explained by the lack of maturity of NS as a field (Vespignani in Klarreich, 2018).

The idea of a disciplinary divide is popular after the first dispute (Keller, 2007). It may explain why the academic activity between 2007 and 2016 aims at filling a knowledge gap (most notably in Barrat et al., 2008; Clauset et al., 2009; Perc, 2014; Stumpf and Porter, 2012). The same actors were surprised when the controversy reignited in 2018, which suggests that they believed they had ended it. Klarreich (2018) quotes Vespignani: "the important question is not whether a network is precisely scale-free but whether it has a heavy tail . . . I thought the community was agreeing on that." Similarly, Holme (2019) states: "I, and (I believe) most colleagues, were following the principle that 'knowledge of whether or not a distribution is heavy-tailed is far more important than whether it can be fit using a power law' . . . Thus, it was surprising that the scale-free debate would flare up again."

First dispute: Power-law and log-normal distributions, 2005

The dispute is about the claim that observed power laws are log-normal distributions. Some argue a flaw

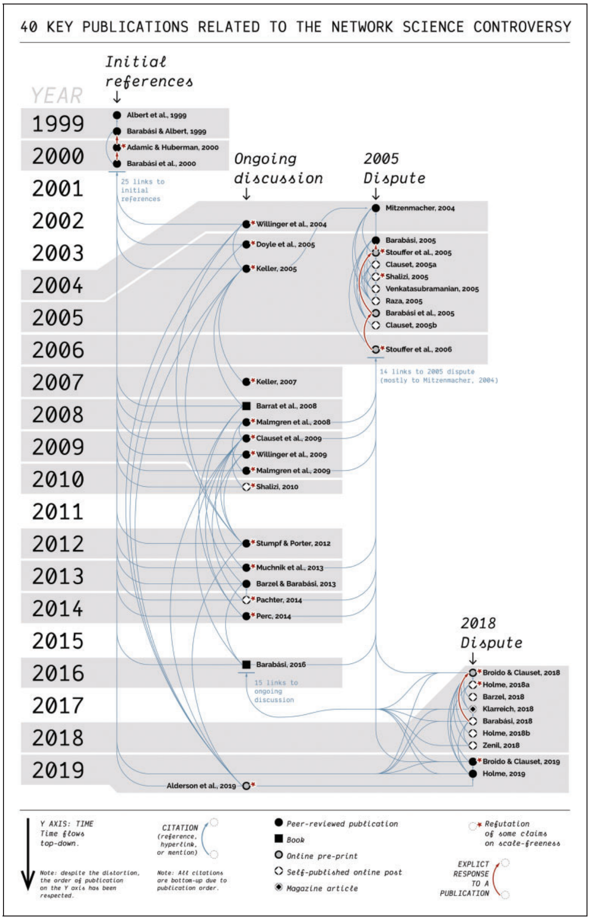

Figure 3. Corpus of 40 documents coded for this study, in chronological order. It includes type of document, direct and indirect refutations, and mentions of other documents in the corpus.

exists in the statistical procedure used to identify power laws, thus challenging their pervasiveness. The dispute unfolds as follows.

In May 2005, Barabási (2005) publishes an article on the presence of "heavy tails in human dynamics".

In October, Stouffer et al. (2005: 1) publish on the online repository arXiv[1] (no peer review) a refutation of Barabási's claim that "the dynamics of a number of human activities are scale-free." They argue that "the reported power-law distributions are solely an artifact of the analysis of the empirical data."

In the days following the release of Stouffer et al.'s pre-print, other researchers comment on the dispute on their respective blogs (Clauset, 2005a; Shalizi, 2005; Venkatasubramanian, 2005). Clauset (2005a) frames it as a matter of "good empirical research" and summarizes the main sticking point as such: "[Stouffer et al.] eliminate the power law as a model, and instead

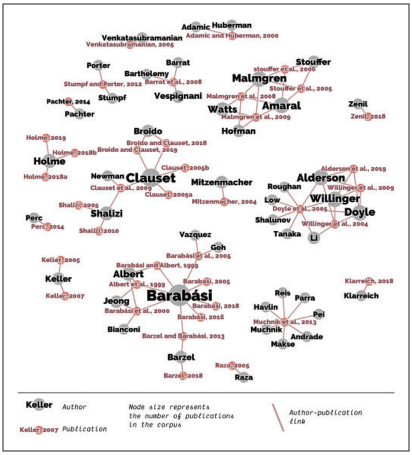

Figure 4. Authors and their publications in the corpus. Note: it does not include authors quoted in a publication.

show that the distributions are better described by a log-normal distribution."

Venkatasubramanian includes Mitzenmacher in the controversy. Venkatasubramanian interviews Mitzenmacher, defending the impossibility of contrasting the two distributions in practice, as he had established in a previous publication (Mitzenmacher, 2004).

In November, Barabási et al. (2005: 2) publish a response to Stouffer et al.'s rebuttal, on arXiv as well. First, they acknowledge that both distributions match observations, but add that Stouffer et al.'s claim stems from a misunderstanding of the original data set. Second, they argue that their work "fails to propose an alternative mechanism indicating that a lognormal distribution could also emerge," and therefore, "is a mere exercise in statistics, one that has little hope to be conclusive" on a larger data set. From that point in time, Mitzenmacher's argument on the relative irrelevance to contrast the log-normal and power-law distributions meets consensus in the community.

In a second blog post, Clauset (2005b) comments on the dispute, and like Mitzenmacher, reframes it to account for the role of Barabási's rhetoric in the reception of his work:

> Barabasi is not one to shy away from grand claims of universality. . . .[His work] does not show causality, nor does it provide falsifiable hypotheses by which it could be invalidated. Barabasi's work in this case is suggestive but not explanatory, and should be judged accordingly. To me, it seems that the contention over the result derives partly from the overstatement of its generality, i.e., the authors claims their model to be explanatory.

Clauset criticizes the strong version of the argument of universality, and points at a specific problem with Barabási's laws-seeking approach: It is not falsifiable. However, note that Clauset does not contest the method or its result, qualified as "suggestive" but empirically valid if "judged accordingly".

Between the two disputes

After a second pre-print from Stouffer et al. (2006) refining their argument, the dispute moves to the classic academic space of peer-reviewed publications. At this point, most authors acknowledge that "whether or not a distribution is heavy-tailed is far more important than whether it can be fit using a power law" (Holme, 2019).

A series of publications contest specific claims on scale-freeness. Keller (2005, 2007) refines her epistemic critique of universality. Malmgren et al. (2008, 2009) show that heavy-tailed distributions in complex networks are not necessarily caused by preferential attachment and propose an alternative model. Muchnik et al. (2013) support the point. Alderson et al. (2019) keep refuting the scale-free model in the case of internet, a critique they formulate during every phase of the controversy, but without mentioning either dispute (Doyle et al., 2005; Willinger et al., 2004, 2009).

Clauset solidifies his position with the help of Shalizi and Newman (Clauset et al., 2009). They develop a rigorous framework for testing scale-freeness, confirming certain empirical observations of power laws and ruling out others.

Stumpf and Porter (2012) also publish an article presented in 2018 as the final point on the controversy.[2] "The most productive use of power laws in the real world will . . . come from recognizing their ubiquity . . . rather than from imbuing them with a vague and mistakenly mystical sense of universality" (666).

Despite critiques, Barabási keeps supporting the argument of universality, albeit under a weaker form (Barzel and Barabási, 2013). The situation leads Pachter (2014) to comment on his blog that "Barabási's 'work' is a regular feature in the journals Nature and Science despite the fact that many eminent scientists keep demonstrating that the network emperor has no clothes," echoing the recurrent claim that the pervasiveness of power laws is a "myth" (Lima-Mendez and Van Helden, 2009; Shalizi, 2010; Willinger et al., 2009).

Table 2. Arguments coded in the corpus, with two example quotes for each.

Argument		Example 1	Example 2
Framing of the controversy. . .	. . . as a disciplinary divide	"For Vespignani, the debate illustrates a gulf between the mindsets of physicists and statisticians, both of whom have valuable perspectives." (Klarreich, 2018)	"Listening to the discussion that followed, I found that it was roughly aligned along a disciplinary divide." (Barzel, 2018)
	. . . as a matter of public relations	"A more important second point, however, relates to how good Barabasi is at generating [public relations]." (Mitzenmacher, in Venkatasubramanian, 2005)	"Despite the sometimes sensational claims made about the Internet" (Alderson et al., 2019)
	. . . as a matter of conceptual ambiguity	"[Scale-freeness] actually did mean something very clear once . . . the claim just sort of slowly morphs to conform to all the evidence" (Watts, in Klarreich, 2018)	"Can we find consensus? A first step would obviously be to agree on a precise definition." (Holme, 2019)
Perspective on scale-freeness	Refutation of some claims on scale-freeness	"Here, we demonstrate that the empirical results reported in [Barabási, 2005] are an artifact of the data analysis." (Stouffer et al., 2006)	"In short, whether or not there are power laws in the topology of the router-level Internet, claims of scale-free vulnerability of high-connectivity hubs are not substantiated and inherently flawed." (Alderson et al., 2019)
	It is POSSIBLE to contrast log-normal and power-law distributions	"the apparent power law is merely an artifact of a bad analysis of the data, which . . . is immensely better described by a log-normal distribution" (Shalizi, 2005)	"Even if our data are well fit by a power law it is still possible that another distribution, such as an exponential or a log-normal, might give a fit as good or better. We can eliminate this possibility by using a goodness-of-fit test again" (Clauset et al., 2009)
	It is IMPOSSIBLE to contrast log-normal and power-law distributions	"Lognormal and power law distributions are so closely related that if somebody wrote a paper claiming some distribution is a power law, you can count on somebody else writing a follow-up paper claiming it is actually lognormal (and vice versa)." (Mitzenmacher, in Venkatasubramanian, 2005)	"In summary, in most areas where we encounter fat-tailed distributions, there is an ongoing debate asking which distributions offers the best fit to the data. Frequently encountered candidates include a power law, . . . or a log-normal function. In many systems empirical data is not sufficient to distinguish these distributions." (Barabási, 2016)
	Scale-freeness requires more rigorous statistical procedures	"we argue that network modeling must move beyond efforts that merely match particular statistics of the data." (Willinger et al., 2009)	"A claim that some network is scale free should thus be established using a severe statistical test that goes beyond static degree distributions." (Broido and Clauset, 2019)
	A basic test of scale-freeness still provides scientific value	"I think it's okay to publish a results that is merely suggestive so long as it is honestly made, diligently investigated and embodies a compelling and plausible story" (Clauset, 2005b)	"While it would be desirable to statistically validate the precise form of the degree distribution, often it is sufficient to decide if a given network has an exponentially bounded or a fat-tailed degree distribution." (Barabási, 2016)

(continued)

Table 2. Continued

Argument		Example 1	Example 2
Perspective on universality	Makes the argument of universality	"The fact that a wide range of human activity patterns follow non-Poisson statistics suggests that the observed bursty character reflects some fundamental and potentially generic feature of human dynamics." (Barabási, 2005)	"The fat-tailed distribution characterizing real networks is one of the most profound universalities of network science, underlying many of its most interesting and important phenomena." (Barzel, 2018)
	Distanciation from the argument of universality	"Another major criticism is that the scale-free ideas and the quest for universal laws are a physicist's obsession that cannot apply to network science which deals with a variety of systems governed by very different dynamical processes. Well, that is true, and all knowledgeable physicists would agree on that." (Barrat et al., 2008)	"These results undermine the universality of scale-free networks" (Broido and Clauset, 2018)
Epistemic posture	Some key notions are lacking falsifiability	"Barabasi's work . . . does not show causality, nor does it provide falsifiable hypotheses by which it could be invalidated. Barabasi's work in this case is suggestive but not explanatory, and should be judged accordingly. To me, it seems that the contention over the result derives partly from the overstatement of its generality" (Clauset, 2005b)	"instead of network scientists going back and retracting the early claims . . . the claim just sort of slowly morphs to conform to all the evidence . . . That's bad for science." (Watts, in Klarreich, 2018)
	Empirical measures only make sense when backed by a model	"the observation that a lognormal distribution offers an equally good fit for some users is a mere exercise in statistics. . . . [Stouffer et al.'s pre-print] fails to . . . answer the most important open question . . . : Where would a lognormal distribution come from?" (Barabási et al., 2005)	"it makes no sense to fit indiscriminately a power law to all of them. One must fit the distribution that the theory predicts, which is predictably different for each system." (Barabási, 2018)

Actor(s)	Period	Frame of the controversy… ... as a disciplinary divide	... as a matter of public relations	... as a matter of conceptual ambiguity	*Perspective on scale-freeness* Refutation of some claims on scale-freeness	It is POSSIBLE to contrast log-normal and power-law distributions	It is IMPOSSIBLE to contrast log-normal and power-law distributions	Scale-freeness requires more rigorous statistical procedures	A basic test of scale-freeness still provides scientific value	*Perspective on universality* Makes the argument of universality	Distanciation from the argument of universality	*Epistemic posture* Some key notions are lacking falsifiability	Empirical measures only make sense when backed by a model
Alderson, Doyle & Willinger	1999-2006				X	X		X	X				
	2007-2016		X		X								
	2018-2019	X	X		X			X					
Amaral & Malmgren	1999-2006				X	X		X					
	2007-2016				X	X					X		
	2018-2019												
Barabási	1999-2006						X		X	X			X
	2007-2016		X				X		X	X			X
	2018-2019		X						X				X
Barzel	1999-2006												
	2007-2016									X			
	2018-2019	X	X					X	X	X			
Clauset	1999-2006		X				X	X	X			X	
	2007-2016				X	X		X	X				
	2018-2019			X	X	X		X			X	X	
Holme	1999-2006												
	2007-2016												
	2018-2019	X		X	X			X	X		X		
Mitzenmacher	1999-2006		X				X		X				
	2007-2016												
	2018-2019												
Shalizi	1999-2006				X	X							
	2007-2016	X	X		X	X		X	X				
	2018-2019												
Vespignani	1999-2006												
	2007-2016	X						X	X	X	X		
	2018-2019	X											
Watts	1999-2006			X									
	2007-2016				X	X					X		
	2018-2019		X			X						X	

Figure 5. Statements by key actors per period: before and during the 2005 controversy, between the two controversies, and during the 2018 controversy. Corresponding quotes are available as supplemental material.

Barabási publishes the book *Network Science* (2016) commenting on the first dispute that "as long as there is empirical data to be fitted, the debate surrounding the best fit will never die out" (151) and standing behind the pervasiveness of the power law despite a "decade-long crusade against network science" (16).

The second dispute makes visible why the disagreement persists. Before I get to this point, I must establish how the controversy differs from its depiction by actors, so that we can see beyond the hypothesis of a disciplinary divide.

The actors' positions during the first dispute

I account for the position of key actors on scale-freeness across the two disputes by tracking the four following statements, systematically coded for the 40 publications of the corpus:

1. We CAN contrast the power-law and log-normal distribution in empirical situations.
2. We CANNOT contrast them.
3. Scale-freeness requires a better statistical characterization.
4. A basic test of scale-freeness is useful to science even if it is not perfectly rigorous.

I use these statements as an analytical grid of argumentative positions that key actors may or may not occupy during each dispute. I show this grid visually for ease of understanding. As only the first two statements are mutually exclusive, I juxtapose only them. According to the key actors' narrative, "statisticians" defend the possibility to contrast distributions, and "physicists" argue that it does not matter in empirical situations. I position the statements accordingly, as illustrated in Figure 6.

The beginning of the 2005 dispute follows the narrative of the physicist/statistician divide. Before the dispute, the empirical issues of contrasting log-normal and power-law distributions are not common knowledge (Figure 7(a)). The "statistician" critique (Stouffer et al., 2005) defends the necessity of better procedures (Figure 7(b)). The "physicists'" response minimizes the importance of the log-normal distribution in empirical situations (Venkatasubramanian, 2005; drawing on Mitzenmacher, 2004), and defends the relevance of modeling despite its apparent statistical weakness (Barabási et al., 2005; Figure 7(c)). The argument hinges on the fact that the power law has a model (preferential attachment) while the log-normal distribution does not. At this point of the first dispute, the hypothesis of a disciplinary divide explains well how the controversy unfolds.

This is how actors explain the closing of the disciplinary gap, disregarding their surprise that it reignites later. Vespignagni states, "the important question is not whether a network is precisely scale-free but whether it has a heavy tail" (Klarreich, 2018). Mitzenmacher's point quickly prevails, and both "sides" acknowledge the practical issues of contrasting the debated distributions. Then, to cite Clauset (2005a), one can ask for "good tools and good statistics" while

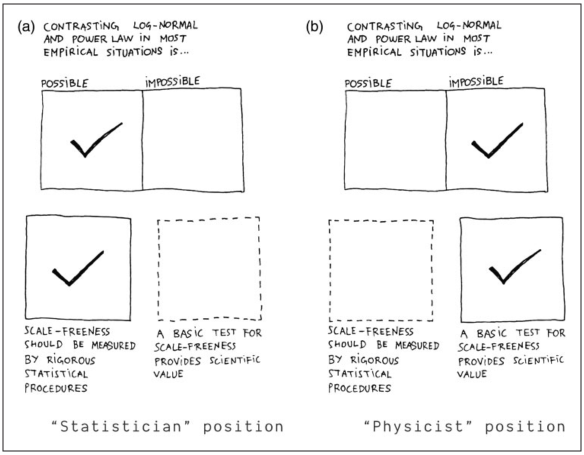

Figure 6. Positions in the narrative of a disciplinary divide. Dashed boxes represent the positions contingent to each side.

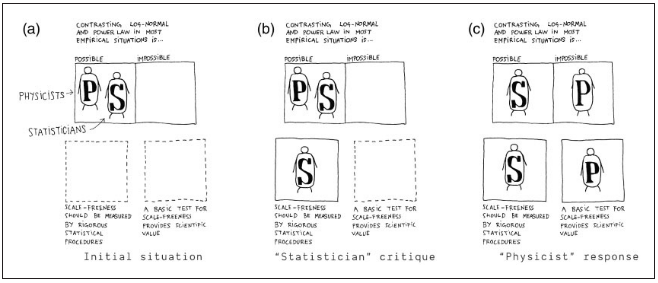

Figure 7. How the first dispute unfolds, **according to the hypothesis of a disciplinary divide**. Dashed boxes represent positions not considered at that point.

acknowledging the benefit of "suggestive" work (Clauset, 2005b). Coexistence between "physicists" and "statisticians" is, after all, possible (Figure 8(a)). As my coding shows (Figure 5), Clauset, Shalizi, and Vespignani acknowledge both positions in their publications (Barrat et al., 2008; Clauset et al., 2009; Shalizi, 2010; see Figure 8(b)). This seems a conscious effort at conciliation, as Vespignani later explains that despite "a gulf between the mindsets of physicists and statisticians . . . both . . . have valuable perspectives" (Klarreich, 2018). This reasonable consensus point is summarized by Stumpf and Porter (2012: 666) as such: "knowledge of whether or not a distribution is heavy-tailed is far more important than whether it can be fit using a power law." Holme (2019) finally comments on it: "I, and (I believe) most colleagues, were following [this] principle."

Why the controversy reignites in 2018 despite this considerable reconciliation effort is worth investigating. I visualize the coding of key actors (Figure 5) using this grid in Figure 9, for convenience. Notice Clauset's trajectory, as he follows the sequence in reverse: He starts in the "happily ever after" position (Figure 8(b)) in 2005 and moves to the typical "statistician" position (Figure 6 (a)) in 2018. The second dispute is triggered by a preprint by Broido and Clauset (2018).

Clauset actively contributes to reaching consensus until the second dispute. He refrains from framing

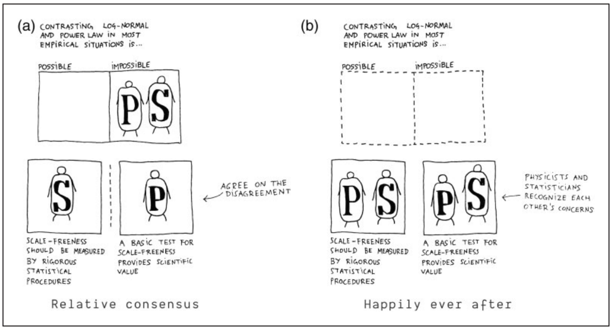

Figure 8. How the controversy was supposed to close, **according to the hypothesis of a disciplinary divide**.

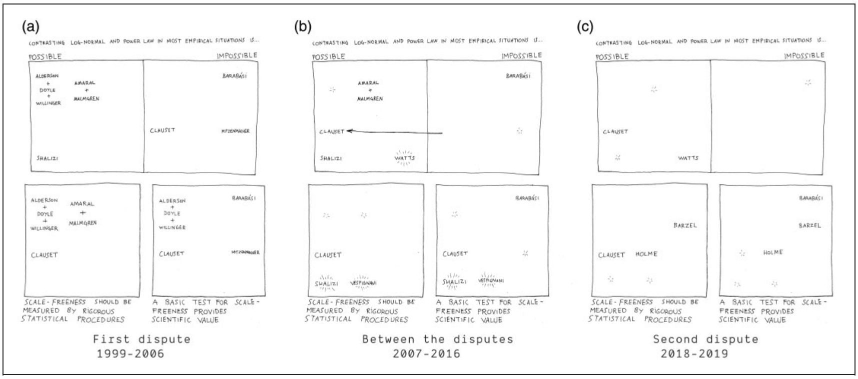

Figure 9. Statements of key actors during three different periods. Some annotation highlights the difference with the precedent period.

the debate as a disciplinary matter and co-publishes with statisticians and physicists. His publications are respected and show an in-depth understanding of Barabási's position. "Power-law Distributions in Empirical Data" (Clauset et al., 2009) is the second most-cited publication of the corpus, cited by Barabási (2016, 2018) twice. However, Clauset (2005b) also requires "falsifiable hypotheses". It is this imperative of falsifiability, and not a disciplinary divide, that grounds his reopening of the controversy.

To understand how a criterion as consensual as falsifiability can become controversial, I need to introduce two approaches to knowledge that renders visible the epistemological commitment of network scientists, notably during the second dispute.

The nomothetic and idiographic subcultures of network science

The type of knowledge Barabási produces determines his position in the controversy. His approach postulates the existence of universal structures: Phenomena obey laws, and the purpose of science is to find them. This position is what the philosopher Windelband introduced as the *nomothetic* approach to knowledge (Lindlof, 2008; see also Munk, 2019), from the Greek "proposition of the law". From that perspective, regularities are how nature tells us its structure, and science tries to understand that language. Barabási is the textbook example of the nomothetic mind. See, for instance, how he presents the power law in his best-seller book *Linked* (2002: 77, emphasis added):

> Nature normally hates power laws. In ordinary systems all quantities follow bell curves, and correlations decay rapidly, obeying exponential laws. But all that changes if the system is forced to undergo a phase transition. Then power laws emerge - nature's **unmistakable sign** that chaos is departing in favor of order. The theory of phase transitions **told us loud and clear** that the road from disorder to order is maintained by the powerful forces of self-organization and is paved by power laws. It **told us** that power laws are **not just another way of characterizing** a system's behavior. They are the **patent signatures** of self-organization in complex systems.

Windelband opposes the nomothetic to the *idiographic* approach to knowledge. This other perspective focuses on accounting for the specifics of phenomena. It is considered typical of the humanities, and the usual idiographic use of networks is to describe (see e.g. Grandjean, 2016; Venturini et al., 2018). Some researchers such as Clauset adopt this approach, as they try to stabilize metrics capable of characterizing scale-free phenomena. Their goal is to improve the descriptive process *regardless* of general implications. Their phenomena may well *dis*obey laws—if that is what experiments find. This independence of generality is what makes their position idiographic.

Galison (1999) remarks that "[e]ach subculture has its own rhythms of change, each has its own standards of demonstration, and each is embedded differently in the wider culture of institutions, practices, inventions, and ideas" (143). He observes how "theorists trade experimental predictions for experimentalists' results" (146). In the second dispute, I find similar interactions between nomothetic theorists, such as Barabási, and the idiographic practice of instrumentalists, such as Clauset.

Second dispute: Characterizing scale-freeness, 2018

The second dispute focuses directly on scale-freeness. It extends the first one, with similar arguments and involves some of the same actors, but unfolds differently.

In 1999, Barabási and Albert publish two famous articles. In the first one (Albert et al., 1999), they study the structure of the World Wide Web and measure that the probabilities of a page to cite or to be cited "follow a power-law over several orders of magnitude" (130). In the second (Barabási and Albert, 1999), they introduce the concept of preferential attachment and measure multiple data sets to conclude that "large networks self-organize into a scale-free state" (510). This article, considered a pillar of network science, states for the first time the disputed point: that scale-freeness is pervasive.

In January 2018, Broido and Clauset publish on *arXiv* the pre-print "Scale-free Networks Are Rare". They retrace the origin and circulation of Barabási and Albert's original statement:

> Across scientific domains and different types of networks, it is common to encounter the claim that most or all real-world networks are scale free. The precise details of this claim vary across the literature . . . Some versions of this "scale-free hypothesis" make the requirements stronger . . . Other versions make them weaker. (1)

To challenge the "scale-free hypothesis," they "carry out a broad test of the universality of scale-free networks by applying state-of-the-art statistical methods to a large and diverse corpus of real-world networks" (2). They conclude that "genuinely scale-free networks are remarkably rare, and scale-free structure is not a universal" (7). The pre-print triggers an instant reaction on the web, notably on Twitter.[3]

In the following days, Holme (2018a) comments in a blog post that "if we could rewrite history and redefine power-laws as 'something that follows a straight line in a log-log histogram if you squint from the side of a computer screen', then they would, for sure, be abundant" (the reconciliation position, see Figure 8 (b)).

In the following days, Barzel (2018) publishes a short piece online aligned with Holme's position: "the meaningfulness of scale-free supersedes its detailed empirical accurateness." He finds the discussion "roughly aligned along a disciplinary divide".

One month after Broido and Clauset's pre-print, Klarreich (2018) publishes a piece in *Quanta Magazine*, presenting and explaining the controversy at length and with great clarity. Despite the absence of peer review, Klarreich writes that "network scientists agree, by and large, that the article's analysis is statistically sound." Like Holme and Barzel, she sees two camps and the disciplinary influence of physics. On one side, "supporters of the scale-free viewpoint, many of whom came to network science by way of physics, argue that scale-freeness is intended as an idealized model." On the other, "critics object that terms like 'scale-free' and 'heavy-tailed' are bandied about in the network science literature in such vague and inconsistent ways as to make the subject's central claims unfalsifiable."

Two months after the publication of the pre-print, Barabási (2018) issues a rebuttal on his website. This self-published piece is more didactic and more polemic than a typical academic publication. For him, Broido and Clauset fail to recognize the scale-free mechanism "[b]y insisting to fit a pure power law to every network, and ignoring what the theory predicts for any of them." Barabási also challenges the relevance of their procedure: "And the real surprise? Even the exact model of scale-free networks, following a pure power law, fails their test.... The true failure is their methodology: It fails to detect that the gold standard is scale-free." He concludes that "the study is oblivious to 18 years of knowledge accumulated in network science." His response ignores the question of falsifiability, and challenges the relevance of the measurement procedure.

In November, Holme (2018b) exposes "the state of affairs" in another blog post: "Simply speaking, there are two camps: those seeing scale-freeness as an emergent property, and those seeing it as a statistical property." On one side, "emergentists ... view scale-free networks essentially as outlined in Barabási and Albert's Emergence of scaling in random networks, ... [and] didn't lose faith in the buzzwords of the nineties' complexity science: universality, fractals, self-similarity, criticality, emergence." On the other, "statisticalists [argue] that scale-freeness is not scientifically important if it is not testable ... [and] are on top of the latest data science trends." He concludes that "[t]he disappointing realization is that whether scale-free networks are rare [or not] is really a choice that needs to be argued by words"—a nice example of Kuhn's (1962) "paradigm incommensurability".

On 4 March 2019, *Nature Communication* publishes two articles: Broido and Clauset's (2019) revised article "Scale-free Networks Are Rare" and Holme's (2019) complementary article, "Rare and Everywhere: Perspectives on Scale-free Networks."

Broido and Clauset's (2019) revised article is substantially the same, retaining the original data and analysis, making the argument clearer and more solid. They clarify that their definition of scale-freeness is not based on preferential attachment and add a "robustness analysis" section implicitly addressing Barabási's technical and conceptual concerns.

Holme (2019) summarizes the controversy and reflects on it. For him, the "controversial topic" is to know whether "scale-free networks rare or universal" and "important or not". He argues that "in the Platonic realm of simple mechanistic models, ... the concepts of emergence, universality and scale-freeness are well-defined and clear. However, in the real world, ... they become blurry.... Now we have one camp ... thinking of scale-free networks as ideal objects ..., and another seeing them as concrete objects belonging to the real world." He suggests finding consensus by acknowledging the legitimacy of studying complexity-related notions, such as scale-freeness, and the need to build a better statistical framework. He remarks finally that "it often feels like the topic of scale-free networks transcends science."

The unresolved tension between idiographic and nomothetic subcultures

The argument of universality is divisive. My coding identified six publications stating it (four co-signed by Barabási), and nine publications criticizing it. Only one does both (Barrat et al., 2008), making a similar point as Holme: Universality is a defined concept "related to the identification of general classes of complex networks" (76), but "all knowledgeable physicists would agree" that "the quest for universal laws ... cannot apply to network science" (296). The other publications mentioning universality pick a side.

Although a formal critique of universality for complex networks exists since at least 2005 (Keller), Barzel and Barabási (2013) disregard it. They acknowledge that "a mathematical framework that uncovers the universal properties of [complex networks] continues to elude us" (673) but do not question the idea itself. *Network Science* (Barabási, 2016) adopts the same position. This lack of dialogue suggests incompatible worldviews.

Keller develops the most precise argument against universality. She identifies a "clash of two cultures" with the "tradition ... in which the search for universal laws has taken high priority," i.e., the nomothetic approach (2007). For her, the argument of universality is invalid, and successful only for reasons external to the criteria for scientific truth. She explains the "faith in ... 'the unique and deep meaning of power laws'" by "the rapid growth of the sector of the publishing industry" and "the remarkably effective uses of language employed in presenting these ideas" (2005: 1067). However, as power laws "are not as ubiquitous as was thought," and it "tells us nothing about the mechanisms that give rise to them," the claim "that scale-free networks are a 'universal architecture' ... are problematic" (2007).

The "clash" is not about the universality of scale-freeness; this is just a disagreement. The clash is about the *scientific status* of the disagreement. Some consider universality disproved; others consider it legitimate. For the first, "the network emperor has no clothes" (Pachter, 2014); the second disregard the critique.

This controversy is a disagreement about a disagreement, and the parties lack common ground to settle their contention. Klarreich (2018) comments on Broido and Clauset's (2018) pre-print, that it "seems to be functioning like a Rorschach test, in which both proponents and critics of the scale-free paradigm see what they already believed to be true." Clauset and Barabási do not see scale-freeness from the same perspective.

Clauset and Watts focus on falsifiability, in the classic Popperian sense. It shows that they see universality as a hypothesis, an evaluable statement. Clauset remarks early that Barabási's work does not "provide falsifiable hypotheses" and later, that the "scale-free hypothesis" (Broido and Clauset, 2018) "sounds like a nonfalsifiable hypothesis" (Klarreich, 2018). Watts criticizes that "the claim just sort of slowly morphs to conform to all the evidence, while still maintaining its brand label surprise factor" (Klarreich, 2018).

In contrast, Barzel and Barabási's (2013) nomothetic approach proceeds by postulating universality, for instance, when they seek "a mathematical framework that uncovers the universal properties of [complex networks]". Barabási's position on modeling also shows this. I coded the argument that *empirical measures only make sense when backed by a model*: Only Barabási states it during each period (see Figure 5). He sees attempts to measure scale-freeness without a model as "a mere exercise in statistics" (Barabási et al., 2005), because for him, the meaning of the findings derives from the postulate of universality embodied in the model. The postulate is part of his way to know.

The different sides of the dispute implicitly disagree on the validity conditions applicable to universality. For Clauset and Watts, universality is a hypothesis that can be proven or disproven. For Barzel and Barabási, it is an epistemic device.

The *nomothetic* approach to knowledge postulates the existence of universal laws, but it does not *state* their empirical reality. Keller's (2005) critique that it is a "faith" is a misinterpretation. The postulate of universality determines an experimental program: which experiments to conduct and how to interpret them. But they can fail. Universality may "elude us" (Barzel and Barabási, 2013). Even so, it drives the scientific process. Questioning the postulate of universality is questioning the entire nomothetic approach. As the latter has been undeniably successful in physics, it confers on universality a remarkably solid foundation. This may explain why Holme and Vespignani defend universality.

Conversely, Keller does not acknowledge universality as a constituent of the nomothetic epistemology. She presents the physicist's "traditional holy grail of universal 'laws'" (2007) as if it were a horizon, while it is, instead, part of their way. Asking Barabási to abandon his "faith in, as he says, 'the unique and deep meaning of power laws'" (2005: 1066) can be only as successful as asking a physicist to reprove physics.

Keller's position is *idiographic*, as characterized by Windelband. She opposes Barabási's universalism with the importance of the specific. She defends the relevance of studying phenomena in their uniqueness and demands that we ponder "when it is useful to simplify, to generalize, to search for unifying principles, and when it is not" (2007).

Contrary to Keller, Clauset seems to fully understand the nomothetic approach, and to acknowledge it. As we have seen, he defends Barabási's early "apparent arrogance" and legitimacy to publish a finding "that is merely suggestive so long as it is honestly made, diligently investigated and embodies a compelling and plausible story." However, Clauset (2005b) also demands "falsifiable hypotheses by which [Barabási's claims] could be invalidated." His refutation in 2018 does not touch upon the postulate of universality, but its empirical validity conditions.

The nomothetic quest for universal laws requires by nature changing theory in the face of evidence: The better model replaces the worse. Evidence always has some degree of looseness in this context, as laws are only as good as the experiments. Barabási opposes this argument to Clauset, insisting that his "findings do not undermine the idea that scale-freeness underlies many or most complex networks" (Klarreich, 2018). But "Clauset doesn't find this analogy convincing" and replies that "it is reasonable to believe a fundamental phenomenon would require less customized detective work" (Klarreich, 2018). Clauset et al. (2009) defend a decade-old agenda of assessing the experimental validity of scale-freeness.

Barabási's experimental program is derived from theory (it is, nevertheless, empirical). His pioneering work on scale-freeness (Barabási and Albert, 1999) prompted multiple authors to seek it in various contexts. The subsequent wave of empirical findings reinforced his claim for the pervasiveness of complex networks (list in e.g. Lima-Mendez and Van Helden, 2009). As Galison (1999) observed in another context, theorists (Barabási) "trade experimental predictions" (pervasiveness) "for experimentalists' results" (146).

The experimental program gradually affirmed by Clauset is that of an experimentalist. It leaves behind the model-based goals of theorists and focuses instead on experimental validity—Popperian falsifiability. By reclaiming the right to invalidate theory by experiment, Clauset challenged Barabási's nomothetic program and set foot on idiographic ground.

Galison (1999: 146) makes relevant remarks on the situation:

> the two subcultures may altogether disagree about the implications of the information exchanged or its epistemic status. For example, . . . theorists may predict the existence of an entity with profound conviction because it is inextricably tied to central tenets of their practice . . . The experimentalist may receive the prediction as something quite different, perhaps as no more than another curious hypothesis to try out on the next run of the data-analysis program. But despite these sharp differences, it is striking that there is a context within which there is a great deal of consensus. In this trading zone, phenomena are discussed by both sides. . . . It is the existence of such trading zones, and the highly constrained negotiations that proceed within them, that bind the otherwise disparate subcultures together.

The controversy reveals tensions between the agendas of different subcultures where distinct approaches to knowledge prevail. Galison suggests that such epistemic rifts are the norm rather than the exception. These epistemic tensions existed before the controversy, and I see no reason to doubt they can survive it.

Barzel (2018), Vespignani, Watts (Klarreich, 2018), and Holme (2019) acknowledge the importance of Broido and Clauset's (2018, 2019) work. Of course, it promises better validity standards for the field. But more importantly, by declaring a new experimental program, their work shows the way out of the long-lasting controversy.

I suggest a plausible interpretation of the controversy. The accumulation of evidence against the universality of scale-freeness weakened Barabási's empirical program. However, most actors still agree on the pervasiveness of complex networks—whatever that means. As Broido and Clauset's program is resilient to the critique of universality, actors may adopt it to design their own experiments. I see theorists and experimentalists as the two legs of the field. When the theoretical leg weakened, the weight naturally shifted to the experimental leg. The controversy made visible an otherwise latent difference of perspective.

Conclusion

In this article, I account for a long-lasting controversy in network science on the nature of scale-freeness. The first dispute in 2005 focuses on the similarity of the power-law and log-normal distributions; the second, in 2018, on the statistical characterization of scale-freeness. Many network scientists have commented on the situation, generally framing it as a conflict between physicists and statisticians, and assuming that the controversy had been settled around 2010. Thus, they were surprised by its resurgence.

I propose another interpretation that better accounts for the resilience of the controversy. The core disagreement lies in the epistemic status of scale-freeness: a sign of a universal law for some, characterization of empirical phenomena for others. Like Galison (1999), I observe epistemic subcultures with different approaches to knowledge. Theorists elaborate models and predictions. Experimentalists stabilize the procedures necessary to account for empirical phenomena. These subcultures do not have the same epistemic perspectives, or the same goals.

We can describe these stances with what the philosopher Windelband introduced as *nomothetic* and *idiographic* approaches to knowledge (Lindlof, 2008). Theorists seek universal laws whose existence they postulate. Experimentalists favor accurate and local descriptions of phenomena. In that sense, network science is a trading zone where theorists trade predictions for experimentalists' results.

I argue that the controversy was caused by the rise of an experimental program challenging the theory-driven approach dominant in the field. Theorists (e.g., Barabási) insist that experiments on scale-freeness draw their validity only from a model. Experimentalists (e.g., Clauset) defend the measurement of scale-freeness with model-independent methods. This disagreement on the epistemic status of scale-freeness existed before the dispute, but became visible as each party argued for their own program. The recent endorsement of Clauset's endeavor by theorists (e.g., Holme) suggests a shift in the field in favor of the experimentalist perspective.

The dynamic of network science offers several lessons in the era of digitization of the social sciences and humanities. Commonplace is the defiance of some scholars regarding the methodological imperialism of natural sciences, or what they perceive as such. The critique has merit, but it might be misplaced in the case of network science, as epistemic gaps do not run along disciplinary lines. Nomothetic positions in the social sciences cause trouble, but powerful idiographic positions also exist within the natural sciences. When something like the network circulates inside science, it moves with an assemblage of theories, experimental results, and material-semiotic practices, including tools. This assemblage is equivocal by nature, and can be received in different ways. Freeman (2008) documented how network centrality circulated from social network analysis to network science and to physics, supporting idiographic practices in physics as it supports nomothetic practices in sociology.

Transdisciplinary fields like digital methods and computational social science are natural zones of dialogue where network practices and predictive models trade knowledge despite their different epistemic perspectives. As this hybridity is sometimes misconstrued as a threat to idiographic practices, I find it useful to remind that idiographic practices exist in the natural sciences, that influence can go both ways, and that we can collaborate without abdicating our respective approaches to knowledge—whatever they are.

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Notes

1. arXiv (pronounced "archive") is an open access, online repository where scholars can upload pre-prints. There is moderation but no peer review. In some disciplines, almost all the articles are self-archived on it. https://arxiv.org
2. By Holme, as quoted by Klarreich (2018); see the second dispute.
3. The web changed between the two disputes. The 2005 dispute is discussed on researchers' blogs; Twitter does not exist. The 2018 dispute is discussed on Twitter first, then on other platforms (e.g., Quora), and on just a few blogs. In the meantime, researchers switched from blogs to Twitter, like most bloggers. Klarreich's (2018) piece in *Quanta* mentions this collection of tweets: https://twitter.com/manlius84/timelines/952248309720211458

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Supplemental material

Supplemental material for this article is available online.

References

Adamic LA and Huberman BA (2000) Power-law distribution of the world wide web. *Science* 287(5461): 2115.

Albert R, Jeong H and Barabási AL (1999) Internet: Diameter of the world-wide web. *Nature* 401(6749): 130.

Alderson DL, Doyle JC and Willinger W (2019) Lessons from "a first-principles approach to understanding the internet's router-level topology". *ACM SIGCOMM Computer Communication Review* 49(5): 96–103.

Bak P, Tang C and Wiesenfeld K (1987) Self-organized criticality: An explanation of 1/f noise. *Physical Review Letters* 59(4): 381–384.

Barabási AL (2002) *Linked: The New Science of Networks*. New York, NY: Perseus Books Group.

Barabasi AL (2005) The origin of bursts and heavy tails in human dynamics. *Nature* 435(7039): 207.

Barabási AL (2016) *Network Science*. Cambridge: Cambridge University Press.

Barabási AL (2018) Love is all you need: Clauset's fruitless search for scale-free networks. *Barabási Lab Commentary*. Available at: https://www.barabasilab.com/post/love-is-all-you-need (accessed 14 July 2020).

Barabási AL and Albert R (1999) Emergence of scaling in random networks. *Science (New York, N.Y.)* 286(5439): 509–512.

Barabási A-L, Albert R, Jeong H, et al. (2000) Response to power-law distribution of the world wide web. *Science* 287(5461): 2115.

Barabási AL, Goh KI and Vazquez A (2005) Reply to Comment on "The origin of bursts and heavy tails in human dynamics." arXiv preprint physics/0511186.

Barrat A, Barthelemy M and Vespignani A (2008) *Dynamical Processes on Complex Networks*. Cambridge: Cambridge University Press.

Barzel B (2018) Spherical cows are rare. Available at: https://www.barzellab.com/ideas (accessed 14 July 2020).

Barzel B and Barabási AL (2013) Universality in network dynamics. *Nature Physics* 9(10): 673–681.

Baya-Laffite N and Benbouzid B (2017) Imaginer la sociologie numérique. *Sociologie et Sociétés* 49(2): 5.

Borgatti SP, Mehra A, Brass DJ, et al. (2009) Network analysis in the social sciences. *Science (New York, N.Y.)* 323(5916): 892–895.

Börner K, Sanyal S and Vespignani A (2007) Network science. *Annual Review of Information Science and Technology* 41(1): 537–607.

Bounegru L, Venturini T, Gray J, et al. (2017) Narrating networks: Exploring the affordances of networks as storytelling devices in journalism. *Digital Journalism* 5(6): 699–730.

Brandes U, Robins G, Anif AM, et al. (2013) What is network science? *Network Science* 1(1): 1–15.

Broido AD and Clauset A (2018) Scale-free networks are rare. Available at: https://arxiv.org/abs/1801.03400 (accessed 14 July 2020).

Broido AD and Clauset A (2019) Scale-free networks are rare. *Nature Communications* 10(1): 1017.

Burrows R and Savage M (2014) After the crisis? Big data and the methodological challenges of empirical sociology. *Big Data & Society* 1(1). Available at: https://journals.sagepub.com/doi/10.1177/2053951714540280.

Clauset A (2005a) Links, links, links. Available at: https://www.cs.unm.edu/~aaron/blog/archives/2005/10/links_links_lin.htm (accessed 14 July 2020).

Clauset A (2005b) Irrational exuberance plus indelible sniping yields delectable entertainment. Available at: https://www.cs.unm.edu/~aaron/blog/archives/2005/11/irrational_exub.htm (accessed 14 July 2020).

Clauset A, Shalizi CR and Newman ME (2009) Power-law distributions in empirical data. *SIAM Review* 51(4): 661–703.

Doyle JC, Alderson DL, Li L, et al. (2005) The "robust yet fragile" nature of the internet. *Proceedings of the National Academy of Sciences of the United States of America* 102(41): 14497–14502.

Erdős P and Rényi A (1960) On the evolution of random graphs. *Publications of the Mathematical Institute of the Hungarian Academy of Science* 5(1): 17–60.

Erikson E (2013) Formalist and relationalist theory in social network analysis. *Sociological Theory* 31(3): 219–242.

Feigenbaum MJ (1976) Universality in complex discrete dynamics. In: *Los Alamos theoretical division annual report 1975–1976*. Available at: http://chaosbook.org/extras/mjf/LA-6816-PR.pdf (accessed 14 July 2020).

Freeman LC (2000) Visualizing social networks. *Journal of Social Structure* 1(1): 4.

Freeman LC (2008) Going the wrong way on a one-way street: Centrality in physics and biology. *Journal of Social Structure* 9(2): 1–15.

Galison P (1999) Trading zone: Coordinating action and belief (1998 abridgment). In: Biagioli M (ed.) *The Science Studies Reader*. Abingdon: Routledge, pp. 258–275.

Grandjean M (2016) A social network analysis of Twitter: Mapping the digital humanities community. *Cogent Arts & Humanities* 3(1): 1171458.

Hidalgo CA (2016) Disconnected, fragmented, or united? A trans-disciplinary review of network science. *Applied Network Science* 1(1): 1–19.

Holme P (2018a) Power-laws and me. Available at: https://petterhol.me/2018/01/12/me-and-power-laws/ (accessed 14 July 2020).

Holme P (2018b) Steak-pun networks: The state of affairs. Available at: https://petterhol.me/2018/11/08/steak-pun-networks-the-state-of-affairs/ (accessed 14 July 2020).

Holme P (2019) Rare and everywhere: Perspectives on scale-free networks. *Nature Communications* 10(1): 1016.

Keller EF (2005) Revisiting "scale-free" networks. In: *BioEssays*. Hoboken, NJ: John Wiley & Sons, Ltd, pp. 1060–1068.

Keller EF (2007) A clash of two cultures. *Nature* 445(7128): 603. Available at: https://www.nature.com/articles/445603a.

Klarreich E (2018) Scant evidence of power laws found in real-world networks. Available at: https://www.quantamagazine.org/scant-evidence-of-power-laws-found-in-real-world-networks-20180215/ (accessed 14 July 2020).

Kuhn TS (1962) *The Structure of Scientific Revolutions*. London: University of Chicago Press.

Latour B (1987) *Science in Action: How to Follow Scientists and Engineers through Society*. Cambridge: Harvard University Press.

Latour B (1999) On recalling ANT. *The Sociological Review* 47(S1): 15–25.

Latour B (2004) On using ANT for studying information systems: A (somewhat) Socratic dialogue. In: Avgerou C, Ciborra C and Land F (eds) *The Social Study of Information and Communication Technology: Innovation, Actors, and Contexts*. Oxford: Oxford University Press, pp. 62–76.

Law J (1999) After ANT: Complexity, naming and topology. *The Sociological Review* 47(S1): 1–14.

Lazer D, Pentland A, Adamic L, et al. (2009) Computational social science. *Science (New York, N.Y.)* 323(5915): 721–723.

Lima-Mendez G and Van Helden J (2009) The powerful law of the power law and other myths in network biology. *Molecular BioSystems* 5(12): 1482–1493. Available at: https://pubs.rsc.org/en/content/articlehtml/2009/mb/b908681a

Lindlof TR (2008) Idiographic vs. nomothetic science. In: The International Encyclopedia of Communication. Chichester: John Wiley & Sons, Ltd.

Malmgren RD, Hofman JM, Amaral LAN, et al. (2009) Characterizing individual communication patterns. In: *Proceedings of the ACM SIGKDD international conference on knowledge discovery and data mining*, Paris, France, June 2009, pp. 607–615. New York, NY: Association for Computing Machinery.

Malmgren RD, Stouffer DB, Motter AE, et al. (2008) A Poissonian explanation for heavy tails in e-mail communication. *Proceedings of the National Academy of Sciences of the United States of America* 105(47): 18153–18158.

Marres N (2012) On some uses and abuses of topology in the social analysis of technology (or the problem with smart meters). *Theory, Culture & Society* 29(4–5): 288–310.

Marres N and Gerlitz C (2016) Interface methods: Renegotiating relations between digital social research, STS and sociology. *The Sociological Review* 64(1): 21–46.

Masson E (2017) Humanistic data research: An encounter between epistemic traditions. In: Schäfer MT and van Es K (eds) *The Datafied Society: Studying Culture through Data*. Amsterdam: Amsterdam University Press, pp. 109–124.

Merton RK (1968) The Matthew effect in science. *Science* 159(3810): 56–63.

Mitzenmacher M (2004) A brief history of generative models for power law and lognormal distributions. *Internet Mathematics* 1(2): 226–251.

Moreno JL (1934) *Who Shall Survive? a New Approach to the Problem of Human Interrelations*. Washington, DC: Nervous and Mental Disease Publishing Company.

Muchnik L, Pei S, Parra LC, et al. (2013) Origins of power-law degree distribution in the heterogeneity of human activity in social networks. *Scientific Reports* 3(1): 1–8.

Munk AK (2019) In: Towards an idiographic data practice, big data and the power of narrative, IT-University of Copenhagen, Denmark, 21–22 March 2019.

Newman M (2018) *Networks*. Cambridge: Oxford University Press.

Pachter L (2014) The network nonsense of Albert-László Barabási. Available at: https://liorpachter.wordpress.com/2014/02/10/the-network-nonsense-of-albert-laszlo-barabasi/ (accessed 14 July 2020).

Perc M (2014) The Matthew effect in empirical data. *Journal of Royal Society Interface* 11. Available at: https://royalsocietypublishing.org/doi/10.1098/rsif.2014.0378.

Raza SA (2005) Power law vs. log-normal distributions. Available at: https://www.3quarksdaily.com/3quarksdaily/2005/11/powerlaw_vs_log.html (accessed 14 July 2020).
Rieder B and Röhle T (2017) Digital methods: From challenges to Bildung. In: Schäfer MT and van Es K (eds) *The Datafied Society: Studying Culture through Data*. Amsterdam: Amsterdam University Press, pp. 109–124.
Ruppert E, Law J and Savage M (2013) Reassembling social science methods: The challenge of digital devices. *Theory, Culture & Society* 30(4): 22–46.
Shalizi CR (2005) Gauss is not mocked. Available at: https://web.archive.org/web/20060903112736/http:/www.cscs.umich.edu/~crshalizi/weblog/390.html (accessed 14 July 2020).
Shalizi CR (2010) So, you think you have a power law, do you? Well isn't that special? Available at: http://www.stat.cmu.edu/~cshalizi/2010-10-18-Meetup.pdf (accessed 14 July 2020).
Stouffer DB, Malmgren RD and Amaral LAN (2005) Comment on Barabasi. *Nature* 435: 207.
Stouffer DB, Malmgren RD and Amaral LAN (2006) Log-normal statistics in e-mail communication patterns. arXiv preprint physics/0605027.
Stumpf MP and Porter MA (2012) Critical truths about power laws. *Science (New York, N.Y.)* 335(6069): 665–666.
van Geenen D, Gray J, Venturini T, et al. (forthcoming) Staying with the trouble of networks: Situating network practices as contribution to critical data and algorithm studies. *Frontiers in Big Data*.
Venkatasubramanian S (2005) Darwin's and Einstein's (e) mail correspondence rates, or a rumination on power laws. Available at: http://blog.geomblog.org/2005/10/darwins-and-einsteins-email.html (accessed 14 July 2020).
Venturini T (2010) Diving in magma: How to explore controversies with actor-network theory. *Public Understanding of Science* 19(3): 258–273.
Venturini T, Jacomy M, Bounegru L, et al. (2018) Visual network exploration for data journalists. In: Name SEI and Franklin B (eds) The Routledge Handbook to Developments in Digital Journalism Studies. Abingdon: Routledge, pp. 265–283.
Venturini T, Munk AK and Jacomy M (2019) Actor-network vs network analysis vs digital networks are we talking about the same networks? In: Vertesi J and Ribes D (eds) DigitalSTS: A Handbook and Fieldguide. Princeton, NJ: Princeton University Press, pp. 510–523.
Watts D and Strogatz S (1998) Collective dynamics of "small-world" networks. *Nature* 393: 440–442.
Willinger W, Alderson D and Doyle JC (2009) Mathematics and the internet: A source of enormous confusion and great potential. *Notices of the American Mathematical Society* 56(5): 586–599.
Willinger W, Alderson D, Doyle JC, et al. (2004) More "normal" than normal: Scaling distributions and complex systems. *Proceedings – Winter Simulation Conference* 1: 130–141. Available at: https://doi.org/10.1109/wsc.2004.1371310 (accessed 14 July 2020).
Zenil H (2018) Response to: As a network scientist, what are your reactions to the "Scale-free networks are rare" paper by Broido and Clauset? Available at: https://www.quora.com/As-a-network-scientist-what-are-your-reactions-to-the-Scale-free-networks-are-rare-paper-by-Broido-and-Clauset (accessed 14 July 2020).

APPENDIX H. TRANSLATING NETWORKS

This is a short paper published in the *Proceedings of the Digital Humanities Conference* in 2019. The appendix proposes a table of correspondence between visual patterns and statistical metrics.

Grandjean, M. and Jacomy, M. (2019) 'Translating networks: Assessing correspondence between network visualisation and analytics', in *Proceedings of the Digital Humanities Conference*. Available at: https://halshs.archives-ouvertes.fr/halshs-02179024 (Accessed: 12 July 2019).

Translating Networks

Assessing correspondence between network visualisation and analytics

Digital Humanities 2019, Utrecht, Netherlands

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Network interpretation is a widespread practice in the digital humanities, and its exercise is surprisingly flexible. While there is now a wide variety of uses in different fields from social network analysis (Ables et al., 2017) to the study of document circulation metadata (Grandjean, 2016) or literature and linguistic data (Maryl and Elder, 2017), many projects highlight the difficulty of bringing graph theory and their discipline into dialogue. Fortunately, the development of accessible software (Bastian et al., 2009), followed by new interfaces (Rosa Pérez et al., 2018; Wieneke et al., 2016), sometimes with an educational dimension (Beaulieu, 2017; Xanthos et al., 2016), has been accompanied in recent years by a critical reflection on our practices (Weingart, 2011; Kaufman et al., 2017), particularly with regard to visualisation. Yet, it often focuses on technical aspects.

In this paper, we propose to shift this emphasis and address the question of the researcher's interpretative journey from visualisation to metrics resulting from the network structure. Often addressed in relation to graphical representation, when it is not used only as an illustration, the subjectivity of translation is all the more important when it comes to interpreting structural metrics. But these two things are closely related. To separate metrics from visualisation would be to forget that two historical examples of network representation, Euler (1736) and Moreno (1934), are not limited to a graphic reading (the term "network" itself would only appear in 1954 in Barnes' work). In the first case, the demonstration was based on a degree centrality measurement whereas in the second case the author made the difference between "stars" and "unchosen" individuals while qualifying the edges as inbound and outbound relationships.

This is why this paper propose to examine the practice of visual reading and metrics-based analysis in a correspondence table that clarifies the subjectivity of the *translation* while presenting possible and generic interpretation scenarios.

Visual approach: making the global structure readable

The way we read networks has changed over time. Historically the question of network readability was asked in terms of aesthetic criteria. In the word of Jacob Moreno "the fewer the number of lines crossing, the better the sociogram". Even in the nineties, when giving birth to the modern layout algorithm, Früchterman and Reingold (1991) aimed at "minimizing edge crossings" and "reflecting inherent symmetry". However, these criteria do not seem so crucial to practices observed nowadays in digital humanities (and beyond).

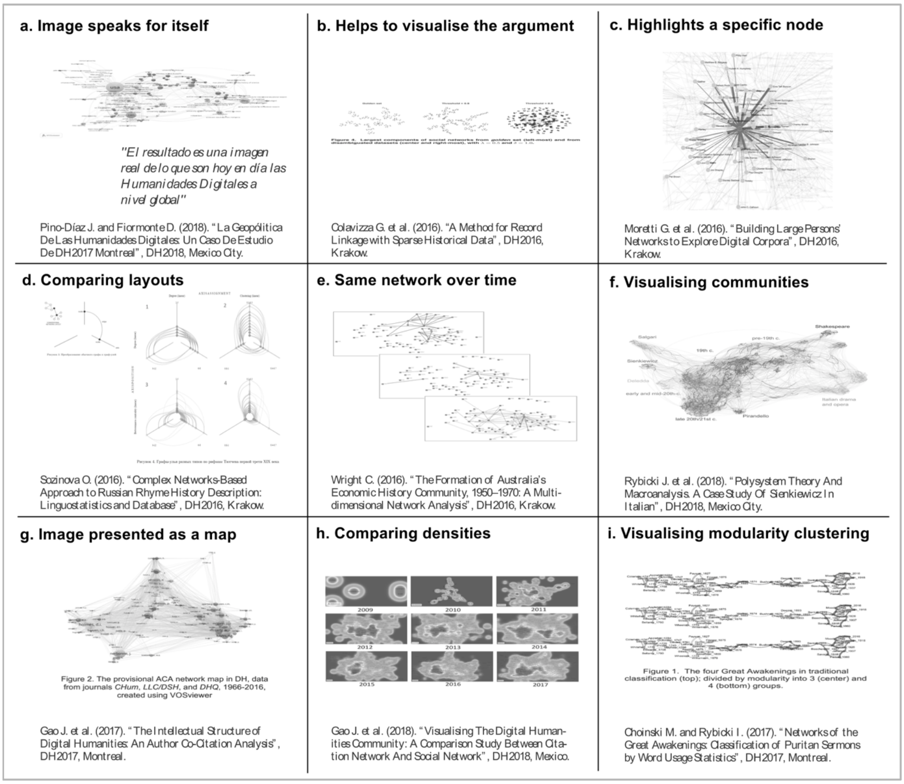


Fig. 1 Different contexts for network visualisation in DH2016, DH2017 and DH2018 abstracts.

Looking at recent papers in digital humanities, networks appear to have a wide range of usages. Their visualisations are either self-sufficient [fig. 1.a.] (Algee-Hewitt, 2018; Pino-Diaz and Fiormonte, 2018; Verhoeven et al., 2018; Marraccini, 2017), an optional help to understanding [fig 1.b.] (Colavizza et al., 2016) or strongly connected to the text. Some authors use them to highlight the position of a specific node [fig. 1.c.] (Moretti et al., 2016), to compare layouts [fig. 1.d.] (Sozinova, 2016) or the layout of the same graph in time [fig. 1.e.] (Wright, 2016). They may aim at visualising communities [fig. 1.f.] (Rybicki et al., 2018; Torres-Yepez and Zreik, 2018), mapping a general structure [fig. 1.g.] (Gao et al., 2017), tracking density patterns [fig. 1.h.] (Gao et al., 2018) or monitoring algorithms like modularity clustering [fig. 1.i.] (Choinski and Rybicki, 2017). These usages reveal a different perspective in network visualisation where we expect the visual to *translate* underlying relational structures.

It helps to give different names to these two different approaches. We call **diagrammatic** the perspective where the network is a diagram that we read by following paths. We do not want the edges to cross and we use aesthetic criteria to bring clarity. It was Moreno's perspective, and is still relevant to small networks and local exploration. Then we call **topological** the perspective where the network is a structure that we read by detecting patterns. We expect the visualisation to help us retrieve structural features like clustering or centralities. It is a common practice in digital humanities, more holistic and relevant to larger networks. Aside or in

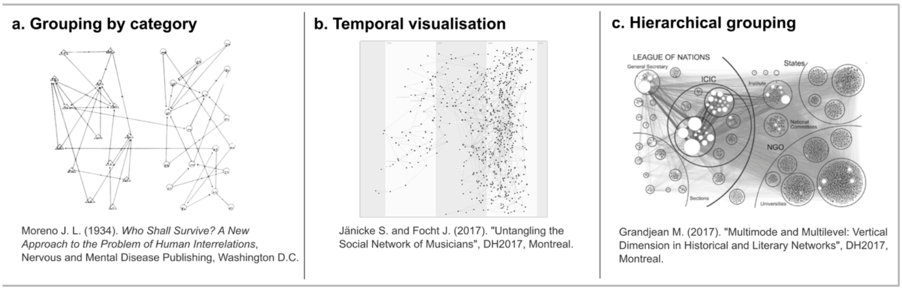


Fig. 2 Various layouts do not follow a force-driven algorithm to make non-relational dimensions of the data explicit.

complement, **classic data visualisation** is also employed to visualise non-relational structures (node attributes, etc.).

In the topological perspective, a standard procedure is to assign nodes a position using a force-driven algorithm. This family of algorithms is known for displaying clusters that match a widely used measure of community detection, modularity clustering (Noack, 2009). Its translation remains however difficult to interpret locally, as we can never give a simple explanation for a node's position. Classic data visualisation also translates non-relational structures, by itself or combined with a relational perspective. Different structural features may require different visualisations: the examples of fig. 2 shows curated visualisations using categories [fig. 2.a boys and girls, in the famous example of (Moreno, 1934)], temporality [fig. 2.b] (Jänicke and Focht, 2017) or hierarchy [fig. 2.c] (Grandjean, 2017). Though very different from force-driven placement, they display better certain structural features.

Objectifying the structure with metrics

Often opposed to visual interpretation, of which they would be a more objective and reliable representation, centrality measures have a history that goes back to more than half a century and shows that they are not immutable and require constant adaptation to usage Moreover, Freeman (1979) insists on the fact that the notion of "centrality" is the result of several intuitive conceptions. To remind that these metrics are based on "intuition" means to recognize that they have no meaning in themselves and that their interpretation must be rediscussed - and therefore translated - according to the context. This paper thus proposes to list and evaluate to which extent these metrics are applicable to humanities and social science data and can, if necessary, be "translated" into this language to complement visual analyses.

Global properties

Statistical analysis allows for comparing networks across multiple dimensions at once (Tank and Chen, 2017). For instance, comparing the **number of nodes and edges** of different graphs of the same type (Trilcke et al., 2016) can be a ranking tool that is directly translatable into natural language. In addition to that, studies suggest that **density** (the number of edges in relation to the number of nodes) is relevant to analyse character networks, especially when compared within a homogeneous collection (Evalyn and Gauch, 2018; Grandjean, 2015). This is also the case when measuring **average path length** (Trilcke et al., 2016).

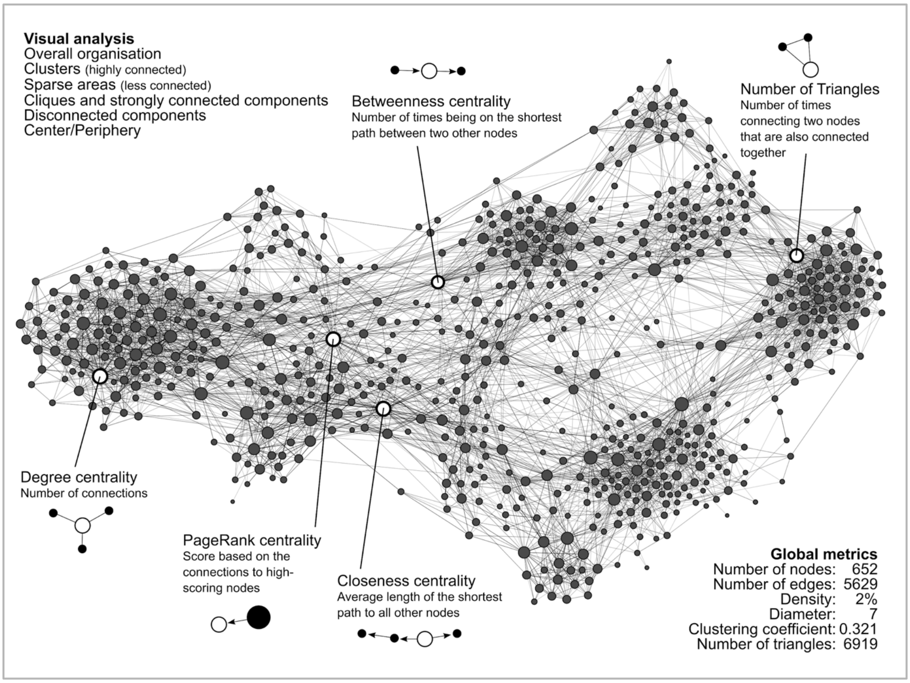


Fig. 3 Three levels of interpretation that can be articulated: visual analysis (examples top left), use of global metrics (examples bottom right) and use of local metrics (highlighted nodes).

Local properties

With regard to local measures, the **degree** (number of neighbouring nodes) is the simplest **centrality**, and the only one systematically used between the late 1950s and early 1970s, before the development of more diversified metrics (Freeman, 1979). Its simplicity allows for a transparent translation: in a literary network, for example, it counts the number of times one character speaks to another (Jannidis et al., 2016).

The notion of **betweenness centrality** disrupts the conception of what the "centre" of a network may consist of. Its ability to reveal structural elements bridging large, immediately visible clusters makes it popular in the social sciences since the emergence of Granovetter's concept of "weak ties" (Granovetter, 1973). Betweenness is very closely linked to the notion of circulation: it counts the shortest paths to detect intermediate "bridges" or "key passages" capable of opening or locking certain parts of the network (Tayler and Neugebauer, 2018). Depending on applications, these are therefore both positions of power and vulnerable places.

The **closeness centrality** allows to highlight the "geographical" middle of the graph. In networks of a certain density and when they are not divided into several distinct communities, the closeness is generally fairly evenly distributed and allows a good translation of the notions of "center" and "periphery".

For its part, the **eigenvector centrality** is quite complicated to translate since it works iteratively and is very much dependent on the structural context at short and medium range around a node. "Prestige" or "influence" centrality, named "power" centrality by its author (Bonacich, 1972), it qualifies a node's environment while operating in cascade: a well-connected node gives its neighbours a part of its authority capital, and so on. It is therefore particularly useful when trying to analyse the hierarchy of the nodes in a graph (Piper et al., 2017). The most well-known use of this measure is the backbone of the Google search engine: the PageRank algorithm (Brin and Page, 1998).

Towards mixed approaches

This contribution proposes a table of correspondence between the concepts of graph theory and the practice of visual network analysis in the social science and humanities. This effort must not be understood as a demarcationist attempt at telling the right method from the wrong. The "dictionary" is not exhaustive and only aims at helping to bridge two worlds that have more in common that what meets the eye. By focusing on *translating* methods, we want to stress that crossing points are real even though they do not come without issues, and thus require our methodological attention.

We also note that the analysis should not be limited to a catalogue of well-known methods (basic centralities, etc.) but that approaches combining several of those should be encouraged to obtain an optimal and innovative "translation". In this way, we could compare metrics (Escobar and Schauf, 2018) or combine them to establish rankings (Fischer et al., 2018; Grandjean, 2018: 328). Furthermore, the enrichment of the networks by means of categories that are not dependent on the structure, like the gender of individuals in a social network (Dunst and Hartel, 2017) or the discipline of projects in a scientometric analysis (Grandjean et al., 2017), allows to test translation and interpretation hypotheses by avoiding the blind approach of testing all possible graph metrics.

References

Ables M. et al. (2017). Using Archival Texts to Create Network Graphs of Musicians in Early Modern Venice, *Digital Humanities 2017*, Montreal.

Algee-Hewitt M. A. (2018). The Hidden Dictionary: Text Mining Eighteenth-Century Knowledge Networks, *Digital Humanities 2018*, Mexico City.

Barnes J. A. (1954). Class and Committees in a norwegian Island Parish, *Human Relations*, 7, 39-58.

Bastian M. et al. (2009). Gephi: an open source software for exploring and manipulating networks, *International AAAI Conference on Weblogs and Social Media*, 361-362.

Beaulieu M.-C. (2017). Perseids and Plokamos: Weaving pedagogy, data models and tools for social network annotation, *Digital Humanities 2017*, Montreal.

Bonacich P. (1972). Factoring and weighting approaches to status scores and clique identification, *The Journal of Mathematical Sociology*, 2, 1, 113-120.

Brin S. and Page L. (1998). The Anatomy of a Large-Scale Hypertextual Web Search Engine, *Seventh International World-Wide Web Conference*, Brisbane.

Choinski M. and Rybicki I. (2017). Networks of the Great Awakenings: Classification of Puritan Sermons by Word Usage Statistics, *Digital Humanities 2017*, Montreal.

Colavizza G. et al. (2016). A Method for Record Linkage with Sparse Historical Data, *Digital Humanities 2016*, Krakow.

Dunst A. and Hartel R. (2017). Corpora and Complex Networks as Cultural Critique: Investigating Race and Gender Bias in Graphic Narratives, *Digital Humanities 2017*, Montreal.

Escobar Varela M. and Schauf A. (2018). Network Analysis Shows Previously Unreported Features Of Javanese Traditional Theatre, *Digital Humanities 2018*, Mexico City.

Euler L. (1736). Solutio Problematis ad Geometriam Situs, *Opera Omnia*, 7, 128-140.

Evalyn L. and Gauch S. (2018). Analyzing Social Networks Of XML Plays: Exploring Shakespeare's Genres, *Digital Humanities 2018*, Mexico City.

Fischer F. et al. (2018). To Catch A Protagonist: Quantitative Dominance Relations In German-Language Drama (1730–1930), *Digital Humanities 2018*, Mexico City.

Freeman L. C. (1979). Centrality in Social Networks: Conceptual Clarification, *Social Networks*, 1, 215-239.

Früchterman T. M. and Reingold E. M. (1991). Graph drawing by force-directed placement, *Software: Practice and Experience*, 21, 1129-1164.

Gao J. et al. (2017). The Intellectual Structure of Digital Humanities: An Author Co-Citation Analysis, *Digital Humanities 2017*, Montreal.

Gao J. et al. (2018). Visualising The Digital Humanities Community: A Comparison Study Between Citation Network And Social Network, *Digital Humanities 2018*, Mexico City.

Grandjean M. (2015). Network Visualization: Mapping Shakespeare's Tragedies, http://www.martingrandjean.ch/network-visualization-shakespeare.

Grandjean M. (2016). Archives Distant Reading: Mapping the Activity of the League of Nations' Intellectual Cooperation, *Digital Humanities 2016*, Krakow.

Grandjean M. (2017). Multimode and Multilevel: Vertical Dimension in Historical and Literary Networks, *Digital Humanities 2017*, Montreal.

Grandjean M. et al. (2017). Complex Network Visualisation for the History of Interdisciplinarity: Mapping Research Funding in Switzerland, *Digital Humanities 2017*, Montreal.

Grandjean M. (2018). *Les réseaux de la coopération intellectuelle. La Société des Nations comme actrice des relations scientifiques et culturelles dans l'entre-deux-guerres*, Lausanne.

Granovetter M. S. (1973). The Strength of Weak Ties, *American Journal of Sociology*, 78, 1360-1380.

Jänicke S. and Focht J. (2017). Untangling the Social Network of Musicians, *Digital Humanities 2017*, Montreal.

Jannidis F. et al. (2016). Comparison of Methods for the Identification of Main Characters in German Novels, *Digital Humanities 2016*, Krakow.

Kaufman M. et al. (2017). Visualizing Futures of Networks in Digital Humanities Research, *Digital Humanities 2017*, Montreal.

Marraccini M. (2017). The Victoria Press Circle, *Digital Humanities 2017*, Montreal.

Maryl M. and Eder M. (2017). Topic Patterns in an Academic Literary Journal: The Case Of Teksty Drugie, *Digital Humanities 2017*, Montreal.

Moreno J. L. (1934). *Who Shall Survive? A New Approach to the Problem of Human Interrelations*, Nervous and Mental Disease Publishing.

Moretti G. et al. (2016). Building Large Persons' Networks to Explore Digital Corpora, *Digital Humanities 2016*, Krakow.

Noack, A. (2009). Modularity clustering is force-directed layout. *Physical Review E*, 79(2), 026102.

Pino-Díaz J. and Fiormonte D. (2018). La Geopólitica De Las Humanidades Digitales: Un Caso De Estudio De DH2017 Montreal, *Digital Humanities 2018,* Mexico City.

Piper A. et al. (2017). Studying Literary Characters and Character Networks, *Digital Humanities 2017*, Montreal.

Rosa Pérez J. et al. (2018). Histonets, Turning Historical Maps Into Digital Networks, *Digital Humanities 2018,* Mexico City.

Rybicki J. et al. (2018). Polysystem Theory And Macroanalysis. A Case Study Of Sienkiewicz In Italian, *Digital Humanities 2018*, Mexico City.

Sozinova O. (2016). Complex Networks-Based Approach to Russian Rhyme History Description: Linguostatistics and Database, *Digital Humanities 2016*, Krakow.

Tang M.-C. and Chen K.-H. (2017). A cross-language comparison of co-word networks in Digital Library and Museum of Buddhist Studies, *Digital Humanities 2017*, Montreal.

Tayler F. and Neugebauer T. (2018). Complex Networks Of Desire: Mapping Community In Visual Arts Magazines Fireweed, Fuse, And Border/Lines, *Digital Humanities 2018*, Mexico City.

Torres-Yepez L. and Zreik K. (2018). Estudio Exploratorio Sobre Los Territorios De La Biopirateria De Las Medicinas Tradicionales En Internet : El Caso De America Latina, *Digital Humanities 2018*, Mexico City.

Trilcke P. et al. (2016). Theatre Plays as 'Small Worlds'? Network Data on the History and Typology of German Drama, 1730–1930, *Digital Humanities 2016*, Krakow.

Verhoeven D. et al. (2018). Solving the Problem of the "Gender Offenders": Using Criminal Network Analysis to Optimize Openness in Male Dominated Collaborative Networks, *Digital Humanities 2018*, Mexico City.

Weingart S. B. (2011). Demystifying Networks, Parts I & II, *Journal of Digital Humanities*, 1, 1.

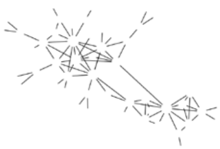
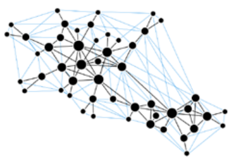
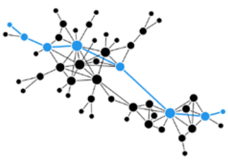
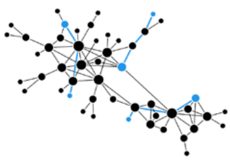
Wieneke, L. et al. (2016). Introducing HistoGraph 2: Exploration of Cultural Heritage Documents Based on Co-Occurrence Graphs, *Digital Humanities 2016*, Krakow.

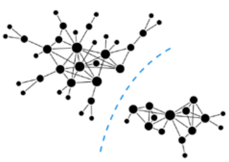
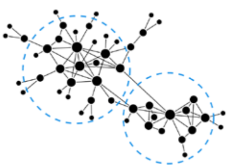
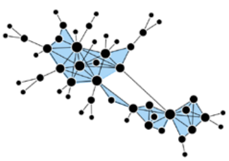
Wright C. (2016). The Formation of Australia's Economic History Community, 1950–1970: A Multidimensional Network Analysis, *Digital Humanities 2016*, Krakow.

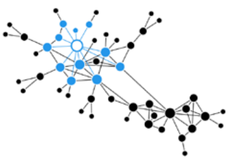
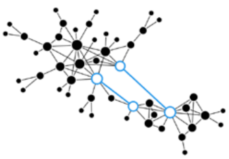
Xanthos A. et al. (2016). Visualising the Dynamics of Character Networks, *Digital Humanities 2016*, Krakow.

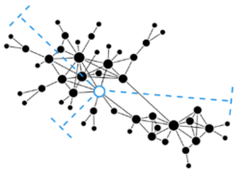
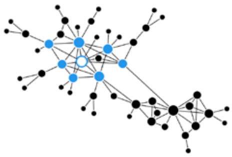
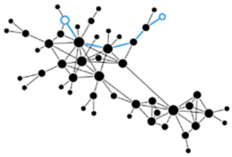
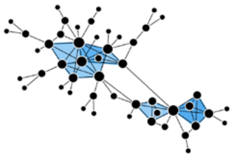
Network visual and topological patterns

This table of correspondence between network analysis concepts and interpretations or "translations" is a work in progress. The authors propose this document to open a discussion on the most relevant translation scenarios and examples/references from the different disciplines applying these methods.

	NOTION		VISUAL ANALYSIS		COMPUTATIONAL ANALYSIS		INTERPRETATIVE POTENTIAL
Global		**Graph size (nodes)** SIMPLE DEFINITION How many nodes are there in the graph?	VISUAL PATTERN There are few or many nodes. HERMENEUTIC CRITERIA Counting the nodes.	ISSUES Though it is easy to have an estimation of the total number of nodes, visualization decisions (for example, setting node sizes on a large scale) can make nodes with few connections difficult to see.	TOPOLOGICAL PATTERN Nodes count. COMPUTATIONAL CRITERIA Counting the nodes.	ISSUES None. Note that in graph theory the count of nodes is referred to as "graph order" while the "graph size" refers to the count of edges.	USEFULNESS Very basic information but useful when comparing networks. "TRANSLATION" The intuition of the **size** of a network is appropriate.
Global		**Graph size (edges)** SIMPLE DEFINITION How many edges are there in the graph?	VISUAL PATTERN There are few or many edges. HERMENEUTIC CRITERIA Counting the edges.	ISSUES The total number is hard to estimate as soon as the graph is not a simple diagram anymore. The distribution of edges and their weight has an influence on the visual estimation. The difficulty to count edges visually is a known issue, and probably impossible to overcome.	TOPOLOGICAL PATTERN Edges count. COMPUTATIONAL CRITERIA Counting the edges.	ISSUES None. Note that in graph theory the count of edges is referred to as "graph size" while the count of nodes is "graph order".	USEFULNESS Very basic information but useful when comparing networks. "TRANSLATION" Sometimes translated as **size** in natural language, but the number of edges is usually expressed in comparison to the number of nodes to indicate density or complexity, not for itself.
Global		**Density** SIMPLE DEFINITION How connected are the nodes overall?	VISUAL PATTERN The graph is more or less compact. If only certain parts are more compact, see "clusters" below. HERMENEUTIC CRITERIA Accumulation of edges, cluttered groups of nodes, "hairball". Easier to estimate in situation of comparison.	ISSUES The less edges there are, the easier to estimate. High densities are difficult to distinguish because the overall appearance of a graph with 60% edges will looks close to a graph with 100%. The visual aspect also depends on the layout algorithm used: some are more efficient at representing clusters.	TOPOLOGICAL PATTERN Network density. COMPUTATIONAL CRITERIA Divide the actual number of edges by the number of all potential edges.	ISSUES The formula of density slightly changes depending on the type of networks (directed or not, self-loops allowed or not...).	USEFULNESS A very important notion that allows to compare networks of different sizes if they are produced in the same way or on the basis of comparable data sets. "TRANSLATION" **Density**, **complexity**, **completeness**.
Global		**Diameter** SIMPLE DEFINITION How far are the most distant nodes?	VISUAL PATTERN The longest shortest path in the graph, or the two most visually distant nodes. HERMENEUTIC CRITERIA Following the series of edges from one node to another, trying to find the longest one. If impossible, the most visually distant nodes is acceptable.	ISSUES Generally hard or impossible to see except on small networks, but quite easy to estimate by following a few paths that goes from a side to another, or just looking at most distant nodes in the same connected component (visual distance approximately correlates with geodesic distance).	TOPOLOGICAL PATTERN Diameter. COMPUTATIONAL CRITERIA Maximal geodesic distance of all the pairs of nodes.	ISSUES Only relevant in a connected graph.	USEFULNESS Can be used to describe how the density is distributed: complex networks are often characterized by a small diameter while high diameter is frequent in geographical networks. "TRANSLATION" **Size, breadth, width.**
Global		**Average path length** SIMPLE DEFINITION On average, how close are nodes to each other?	VISUAL PATTERN The average distance between a couple of nodes. HERMENEUTIC CRITERIA Following the edges between every couples of nodes.	ISSUES Impossible to calculate visually since it is an average covering a very large number of values (already difficult to calculate). Loosely relates to density, which is easier to estimate.	TOPOLOGICAL PATTERN Average path length. COMPUTATIONAL CRITERIA Average number of steps along the shortest paths for all possible pairs of nodes	ISSUES Since it is an average, this value does not allow conclusions to be drawn at the individual level if the graph is strongly clustered. The average path length is more complicated for a directed graph than for an undirected graph.	USEFULNESS Could serve as a complement to diameter because the latter can be influenced by a few nodes that are very far from the main component of the graph. Can replace the diameter in case of unconnected graphs. "TRANSLATION" Can be used to describe the **size**, **breadth** or **width** of the network. But it can also be translated into an indicator of a **small world** situation.

	NOTION		VISUAL ANALYSIS		COMPUTATIONAL ANALYSIS		INTERPRETATIVE POTENTIAL
Global		**Connectedness** SIMPLE DEFINITION Is the graph a connected system where there is a path between every nodes?	VISUAL PATTERN There must be only one component, not several groups of nodes disconnected from each other. HERMENEUTIC CRITERIA Looking at empty areas (structural holes). Groups count as disconnected only if there are no edges between them.	ISSUES Depending on the layout, it is possible that "islands" hide in dense groups of nodes, but with a properly set force-directed layout, the risk is marginal. Possibly the easiest property to observe visually.	TOPOLOGICAL PATTERN In a connected graph, the number of connected components must be one. COMPUTATIONAL CRITERIA There must be a path between each pair of nodes.	ISSUES The notion of connectedness is more complicated for a directed graph than for an undirected graph.	USEFULNESS The absence of edges between components is more remarkable if they contain many nodes. In many applied cases, connected graphs are artificially created by removing solitary nodes (frequent in messy extracted data). "TRANSLATION" The network is a **continent**, or, on the contrary, an **archipelago**.
Global		**Clusters/ Communities** SIMPLE DEFINITION What are the groups where nodes are more connected to each other?	VISUAL PATTERN Clusters (uneven distribution of nodes) HERMENEUTIC CRITERIA Looking for groups of nodes, as visually dense and separated as possible.	ISSUES Force-directed placement algorithms are known to represent clustering very well, if properly set.	TOPOLOGICAL PATTERN Max modularity (modularity of the partition with the highest modularity). COMPUTATIONAL CRITERIA Running a modularity clustering detection algorithm and looking at the obtained modularity.	ISSUES Maximal modularity is too hard to compute, so we rely on an estimation. Modularity is a measure of a graph partitioning, so it is necessary to partition the graph first. Different algorithms exist (Louvain, Leiden...). Other metrics than modularity also exist, though they are less widely used.	USEFULNESS Useful for exploration. It is tempting to take the result of a cluster calculation as a given. In some cases, it is interesting to compare these clusters with previously known groups (categories that do not depend on the structure obtained). "TRANSLATION" The term **cluster** has become part of the common language, but we also like to talk about **groups**, **communities** or **hubs**. This notion of community is very directly related to the way in which the social sciences and humanities use the metaphor of the "network".
Global		**Global or average clustering coefficient** SIMPLE DEFINITION General indication of the graph's tendency to be organized into clusters	VISUAL PATTERN Clusters. HERMENEUTIC CRITERIA Looking for triangles (groups of three nodes with three connexions between them).	ISSUES Triangles are easy to count visually in a small network, but the ratio between this result and the total number of potential triangles is impossible to calculate directly. Very difficult to count in dense graphs. Graphs with clusters and/or visually dense tend to have a higher clustering coefficient.	TOPOLOGICAL PATTERN Number of closed triplets. COMPUTATIONAL CRITERIA Dividing the number of closed triplets by the number of triplets in the graph.	ISSUES The global clustering coefficient is obtained by dividing the closed triplets by the number of all possible groups of three nodes. The average clustering coefficient is quite different but serve a relatively close purpose: it is the average of the local clustering coefficient of all the nodes.	USEFULNESS A global measure that complements density well and, like the latter, is useful for comparing similar networks with each other. "TRANSLATION" Gives an idea of the **entanglement / intrication** and the presence of a more localized **density**.

Local		**Connectivity (degree)** SIMPLE DEFINITION How well connected is a node / how many links it has / how many neighbors	VISUAL PATTERN There are many links to the node. HERMENEUTIC CRITERIA Counting the edges converging to that node.	ISSUES In a dense image, it is not always obvious which edges converge to the node or just happen to pass through it visually. Sometimes, counting is also impractical.	TOPOLOGICAL PATTERN Degree. COMPUTATIONAL CRITERIA Degree.	ISSUES In a directed network, we also distinguish indegree (inbound link) and outdegree (outbound links). In that case, the degree is the sum of those and hence the number of links, not the number of neighbors.	USEFULNESS The simplest form of centrality. In most cases, the degree shows information that is already known as part of the basic data and not dependent on the structure. This is why we often focus on the degree distribution. "TRANSLATION" The basic intuition of the number of **neighbors**. In directed networks, interpretation varies greatly between in- and out- degrees: indegree is often the primary way to look at a hierarchy of nodes, because being "cited" is often a good proxy for **authority/notoriety**.
Local		**Betweenness** SIMPLE DEFINITION Being a bridge, connecting otherwise separated groups of nodes. Removing that node would break many shortest paths.	VISUAL PATTERN A bridge between clusters. HERMENEUTIC CRITERIA Looking for an edge appearing through a (mostly) empty area between large groups of nodes.	ISSUES Many bridges look as expected, they connect over empty spaces. But sometimes, bridges are hidden in the complicated structure of the image. It is generally easier to see the bridging edges than the bridging nodes (however, most of the studies using betweenness centrality focus on bridging nodes).	TOPOLOGICAL PATTERN Betweenness centrality. COMPUTATIONAL CRITERIA The score of betweenness centrality represents the number of shortest paths through a given node or edge.	ISSUES Note that the undirected version of the algorithm is often used even for directed graphs. It is the most used metric for detecting bridges, but it does not exactly meet the intuition.	USEFULNESS The definition of bridge implemented by betweenness centrality meets both intuition of a bridge and of a center. Indeed both a bridge and the center of a star are things that, if removed, disconnect parts of the network. In that sense betweenness is also a "centrality". "TRANSLATION" The notion of **bridge** (but also **link**, **gateway**, **broker** or **key passage**) is very often used when applying network analysis to social or circulation issues. In some cases, it can represent a form of **social capital** because it describes a structural position of **power** (or **vulnerability**).

	NOTION		VISUAL ANALYSIS		COMPUTATIONAL ANALYSIS		INTERPRETATIVE POTENTIAL
Local		**Closeness** SIMPLE DEFINITION Being in the middle of the network.	VISUAL PATTERN The geographical center of the graph. HERMENEUTIC CRITERIA Finding the barycenter (the center of the "land masses") of the graph.	ISSUES The visual estimation of centrality is considered acceptable, but it remains an evaluation. It is harder to find in very sparse graphs.	TOPOLOGICAL PATTERN Closeness centrality. COMPUTATIONAL CRITERIA The score of closeness centrality is the average length of the geodesic distances to all the other nodes.	ISSUES The undirected version is often used even for directed graphs.	USEFULNESS There is no single implementation of centrality, but closeness centrality is the most aligned with the notion of a middle, a point that is in proximity to all the others. It looks at the structural distance to other nodes, and can be interpreted as such. "TRANSLATION" Excellent to describe the **centre** or the **middle** of a network, especially when the latter is described in topographical terms. Low values of this metric are very appropriate for the use of concepts which are the opposite of the center: the **periphery**, the **margins**, etc.
Local		**Prestige (eigenvector)** SIMPLE DEFINITION Being connected to well connected nodes without necessarily having a large number of neighbors itself.	VISUAL PATTERN Proximity to well connected nodes (often inside a cluster). HERMENEUTIC CRITERIA None, except if the size of the nodes is visually proportional to the degree centrality, which helps to identify nodes in the hubs' surroundings.	ISSUES This centrality is hard to see, though it correlates with other forms of centrality that point to well connected nodes at the center of the graph.	TOPOLOGICAL PATTERN Eigenvector centrality or Page Rank. COMPUTATIONAL CRITERIA This is a score computed recursively. It flows from each node to its neighbors (following the direction of edges in a directed graph).	ISSUES None.	USEFULNESS This form of centrality is notably adapted to directed networks, and can be related to the functioning of a search engine (the Page Rank principle was used in the first Google search engine) or a system where information flows. "TRANSLATION" The iterative nature of this notion makes it difficult to translate (and difficult to use in some contexts). It is confused with the notions of **prestige**, **authority**, **influence** and, sometimes, **power** and **elites**. This measure distinguishes nodes that are "**well**" connected (and not just "a lot"). Relates to the notion of **assortativity**.
Local		**Local clustering coefficient** SIMPLE DEFINITION Are the neighbours of a node also connected together?	VISUAL PATTERN Nodes are inside a cluster. HERMENEUTIC CRITERIA Looking for nodes that have many edges to their cluster (where the other nodes are also connected together). Bridges have a low clustering coefficient.	ISSUES Clustering coefficient is generally hard to see and visual interpretation is considered unreliable. Exceptions are small networks, nodes that have only a few neighbors that we see well, and nodes that are only connected to a very dense cluster.	TOPOLOGICAL PATTERN Clustering coefficient (local). COMPUTATIONAL CRITERIA Calculate density of the subgraph of neighbors (how close from complete is the graph formed by the node and its neighbors).	ISSUES None.	USEFULNESS Meets a notion of redundancy in the local connections, comparable to centrality but at a very local scale. Tells if a node is in a clustered environment. Complex networks are often characterized by a high average clustering coefficient. "TRANSLATION" This local measure makes it possible to analyse relationships at the collective level: it can be translated as an indicator of **participation in a group** (or, on the opposite, **loneliness**, **solitude**). It opposes the notion of a bridge.
Local		**Shortest path** SIMPLE DEFINITION Two nodes are connected by a path	VISUAL PATTERN Presence of a path between the two nodes whose relationship is to be analyzed. HERMENEUTIC CRITERIA Following the series of edges from one node to another to find the shortest.	ISSUES Requires that we can follow the links in practice, which is possible only for small (undirected) networks and depends on the graphic settings. Finding a path can be difficult, and ensuring that this path is the shortest can be too difficult. However the visual distance is a loose approximation of the shortest path length.	TOPOLOGICAL PATTERN Shortest path(s). COMPUTATIONAL CRITERIA Geodesic distance, algorithms for shortest path detection.	ISSUES Can be computationally costly on big networks. Note that multiple shortest paths can exist.	USEFULNESS Very adapted to the use of the graph as a research interface to test the relation of couples of nodes. Very close to the qualitative approach of the humanities, which are often focusing on a few individuals in the network. "TRANSLATION" Corresponds to the intuitive notion of **distance** in the graph structure. Note that this translation does not take into account the fact that nodes are not always aware of the steps between them and that the perceived distance is not always the shortest path.
Local		**Cliques** SIMPLE DEFINITION Groups of nodes where all possible edges exist between them.	VISUAL PATTERN Very dense clusters. HERMENEUTIC CRITERIA Looking for groups of nodes where each of them is connected to all the others.	ISSUES Possible for small or sparse networks, especially if the focus is on cliques that are 4+ in size. Visually impossible for complex networks where cliques are very frequent.	TOPOLOGICAL PATTERN Clique (group of nodes with density of 1). COMPUTATIONAL CRITERIA A group of nodes has a density of 1. Clique detection algorithms exist.	ISSUES The number of cliques is often very high. Quasi-cliques are almost as important as cliques. But multiple algorithms deal with this structure (eg. clique percolation).	USEFULNESS The number of cliques, their size and distribution are metrics that are complementary to the clustering coefficients (local and global). They can be used as a more strict community detection algoritm. "TRANSLATION" The term **clique** itself refers to social groups of individuals who knows each other. They can be translated as **communities**, **neighborhoods**, closed **societies**.

APPENDIX I. CONNECTED-CLOSENESS

This is a draft paper intended for submission to the *Journal of Graph Algorithms and Applications* or a similar journal.

Jacomy, M. (unpublished manuscript) ‘Connected-closeness: A visual quantification of distances in network layouts’.

Connected-closeness: A Visual Quantification of Distances in Network Layouts

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Aalborg University, Copenhagen

1 Introduction

This paper proposes the “maximal connected-closeness”, a metric providing a contextual statement about a given network map, i.e. a dot-line graph drawing where nodes have been placed by a force-directed algorithm (or similar). It aims at quantifying the intuition that “most connected nodes are very close”. It defines a distance (Δ_{max}) that captures the best this notion (figure 1).

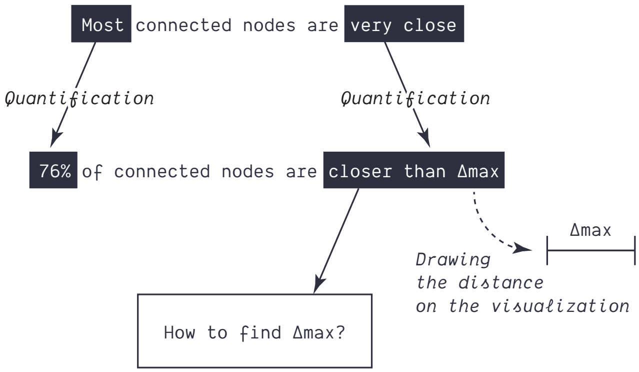


Figure 1: Quantifying an intuitive statement about network maps.

Connected-closeness C is the metric used to define Δ_{max}. It formalizes how close the connected nodes are in the layout (it measures edge shortness). In a nutshell, it accounts for how many edges are shorter than a given distance Δ while discounting the expected number of edges that would be shorter if all edges were rewired at random. Where the function $C(\Delta)$ reaches its maximum, we define Δ_{max} and $C_{max} = C(\Delta_{max})$ is the maximal connected-closeness.

I contend that C_{max} is relevant to characterize layouts as well as networks. Beyond helping scholars to interpret network maps, it can be used as a quality metric to compare different layouts.

I expose my motivation, formalize the problem of finding the maximal connecte closeness, and provide formal definitions. Then I propose a graphic design for network maps and I justify it. Thereafter, I present a practical implementation of the metric. Finally, I highlight the main takeaways of a benchmark I conducted on various networks and layouts, also presented in details as an appendix.

2 Motivation

Most node-placement (embedding) techniques use edge length as a criterion. Stress minimization strategies aim at specially defined distances, while force-driven algorithms aim at the shortest distances possible. From the standpoint of a scholar interpreting the layout visually, this suggests that edge lengths can be interpreted directly. Unfortunately, this assumption is false, which leads to misinterpretations.

Even though a force-driven placement algorithm tries to minimize edge lengths, the constraints are generally too strong for it to succeed. Some edges have to remain long, while many disconnected nodes have to be packed together. This is for instance the case of large star networks in two dimensions (figure 2). More generally, the heavy tailed degree distribution of complex networks creates such constraints.

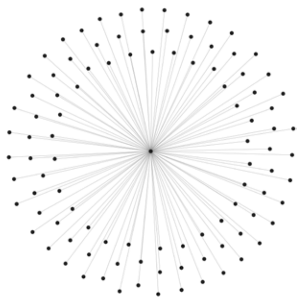


Figure 2: A star network with 100 nodes. Layout: Force Atlas 2. Connected node pairs are less close than many disconnected pairs.

As a consequence, the simple interpretations that come to mind are not necessarily true. It is not true in general that all connected nodes are close, or that disconnected nodes are distant. Two close nodes are not necessarily connected, and two distant nodes are not necessarily disconnected. Certain statements might be true, however, since we expect connected nodes to be closer, on average, than disconnected nodes. Can we build a precise and true statement that captures the effect of the layout?

This work aims at providing a quantified and meaningful statement about node distances, in order to help scholars formulate reproducible interpretations. I do not claim that it is the only possible interpretation, let alone the best, but it is quantified and fits most force-directed placements. This statement is, in short, “most connected nodes are very close.” The “most” and the “very close” are quantified, and the validity of the statement is precisely assessed. I call it visual because “very close” is expressed as a distance that we can plot. The quantifications depend on the layout, and must be calculated.

3 Problem formulation

Our goal is to find a quantified version of the statement "most connected nodes are very close" for a given network and layout.

Let us have a network and a node placement in 2 dimensions. I refer to the distances in this arbitrary space as "Euclidean distances" to differentiate them from other distances such as the geodesic distance (length of the shortest path). For a given Euclidean distance Δ, we can find the exact set of edges (or node pairs) whose Euclidean distance is shorter (figure 3).

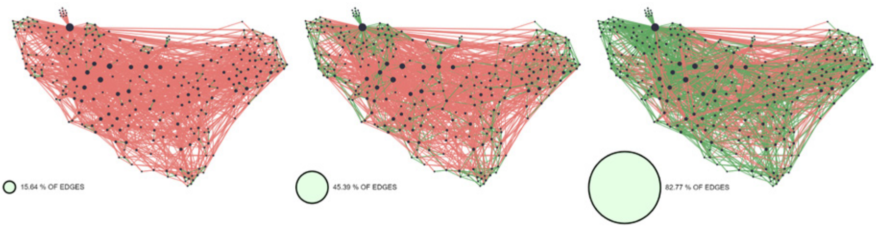


Figure 3: Network: C. Elegans. Layout: LinLog (Force Atlas 2 implementation). A given part of edges are smaller than a given selection distance Δ. The diameter of the circle represents the selection distance Δ. Shorter edges are in green, longer edges in red.

We compute different indicators for each selection distance Δ (see figure 4). The share of edges shorter than Δ is noted $E_{\%}(\Delta)$ and plotted in black. The share of node pairs closer than Δ is noted $p_{\%}(\Delta)$ and plotted in blue. By definition, both quantities are strictly increasing, and $E_{\%}(\Delta)$ is always higher than $p_{\%}(\Delta)$ (black over blue).

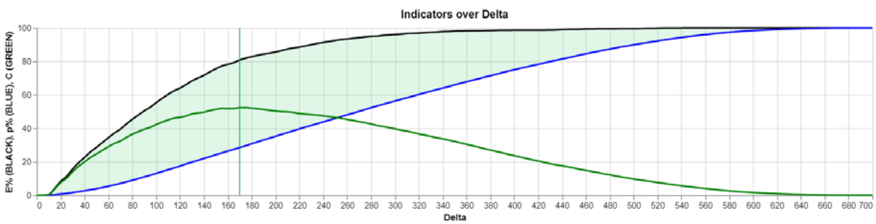


Figure 4: Indicators computed over the selection distance Δ for the network and layout of figure 3.

As $p_{\%}(\Delta)$ (in blue) is a natural point of comparison, the situation presents an opportunity. Indeed, the share of node pairs $p_{\%}(\Delta)$ can be understood as the share of edges *if they were distributed at random*. Let us call this the "expected share of edges shorter than Δ", where "expected" means "in a similar but randomized situation". We can then compare the *actual* proportion of edges to the *expected* proportion. This gives us the green curve, the proportion of edges shorter than Δ above expectations. It is equal to the difference between the black and the blue curve, highlighted as a greenish area, and plotted as the green curve.

The green curve is obviously null at both ends, so it has to reach a maximum in between (plotted as a green vertical line). This point is remarkable. Firstly, the higher the green curve, the more "unexpected" edges captured by the layout (the more dramatic statement we can make). Secondly, it provides the precise distance were the layout is the most efficient, which is a precious practical information on the map. Identifying this point allows forging a quantitative and informative statement such as "$X\%$ of edges are *unexpectedly* shorter than Δ", where X is as high as possible. I propose to call the quantity represented by the green curve "connected-closeness" and turn its maximum into a network layout metric. In practice, the curve may have a plateau, which challenges the existence of a single maximum. I address this issue in the *implementation* section.

4 Definitions

4.1 Naming

$C(\Delta)$ is the *connected-closeness* for the Euclidean distance Δ. It measures the *percentage of unexpectedly close connected nodes*, where close means closer than Δ (see below).

Δ_{max} is the *distance of maximal connected-closeness.*

$C_{max} = C(\Delta_{max})$ is the *maximal connected-closeness.*

4.2 Definition of connected-closeness

$$C(\Delta) = \frac{E(\Delta) - E_{expected}(\Delta)}{E(\infty)} = \frac{E(\Delta)}{E(\infty)} - \frac{p(\Delta)}{p(\infty)} \quad (1)$$

- $E(\Delta)$ is the count of edges shorter than the Euclidean distance Δ
- $E(\infty) = e$ is the total count of edges (i.e. the graph size e)
- $E_{expected}(\Delta) = E(\infty) \times \frac{p(\Delta)}{p(\infty)}$ is the count of *expected* edges shorter than Euclidean distance Δ
- $p(\Delta)$ is the count of node pairs closer than the Euclidean distance Δ
- $p(\infty) = n \times (n-1)$ is the total count of node pairs (n is graph order)

4.3 Definition of the maximal connected-closeness

C_{max} is defined as the maximum of $C(\Delta)$ for all Δ. Δ_{max} is the Euclidean distance where $C(\Delta)$ is maximal. In case of ties, the smallest Δ is retained (see *implementation* for additional details).

4.4 Other quantities

- $E_{\%}(\Delta) = \dfrac{E(\Delta)}{E(\infty)}$ is the proportion of edges shorter than the Euclidean distance Δ (expressed as a percentage).

- $p_{\%}(\Delta) = \dfrac{p(\Delta)}{p(\infty)}$ is the proportion of node pairs closer than the Euclidean distance Δ (expressed as a percentage)

- $P_{edge}(\Delta) = \dfrac{E(\Delta)}{p(\Delta)}$ is the probability that, considering two nodes closer than the Euclidean distance Δ, they are connected.

5 Design and visualization

As the quantification is in part visual (Δ_{max} is relative to the visualization) the graphic design matters. I suggest a few guidelines to make the most out of connected-closeness. These guidelines are implemented in figure 5.

- Δ_{max} should be represented visually. I suggest using a grid, as the repetitiveness of the cells makes it easier to estimate visually whether a given pair of nodes is shorter or longer than Δ_{max}.

- State the meaning of Δ_{max} in plain English. In this case: "54% of connected nodes are closer than Δ_{max} due to the effect of the layout".

- As this statement remains quite complicated, I propose accompanying it with a simpler one, the raw share of edges shorter than Δ_{max}, i.e. $E(\Delta_{max})$.

- As another way to mitigate the complication, a chart may visualize the share of edges that would be closer than Δ_{max} anyway, i.e. $p_{\%}(\Delta_{max})$.

- To mitigate the misunderstanding that Δ_{max} represents a chance, for close nodes, to be connected, I suggest stating that figure as well, i.e. $P_{edge}(\Delta_{max})$. In our example, two nodes closer than Δ_{max} have 9% chances to be connected, which is much lower than the 54% of C_{max}: this statement is a poor description of the layout.

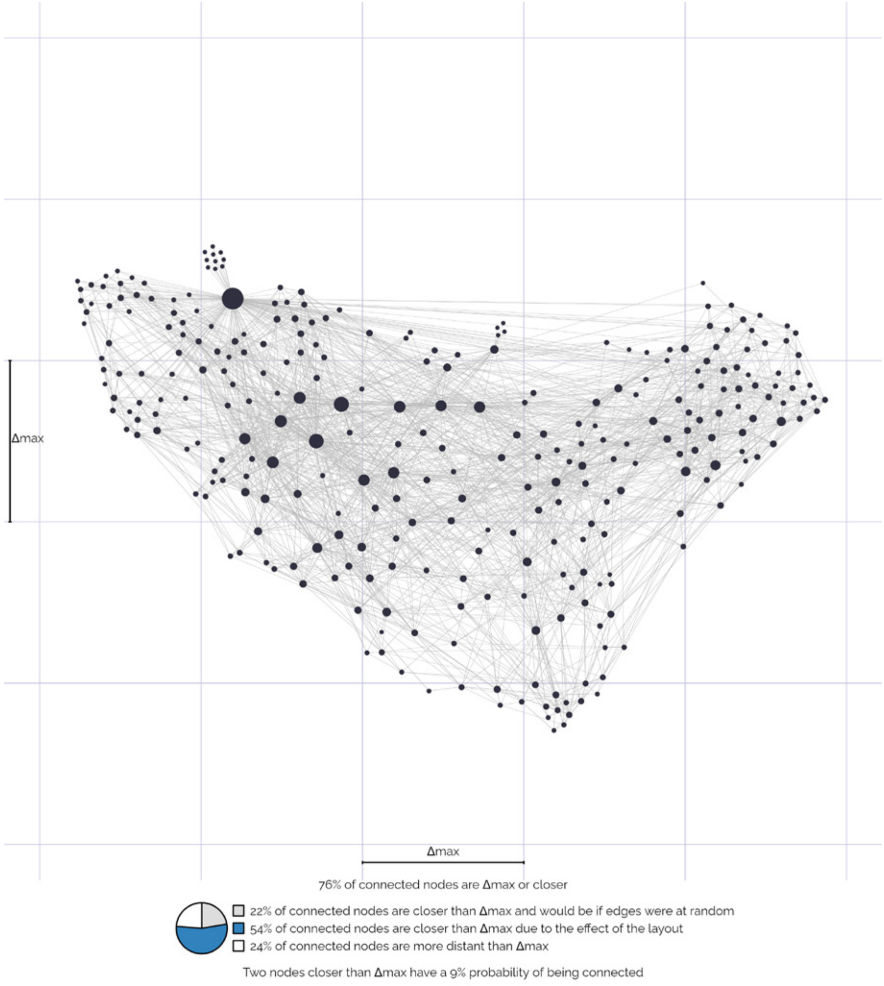


Figure 5: C. Elegans (Layout: LinLog) visualized using Δ_{max} as a grid

5.1 Resistance to misuses

The statement proposed by connected-closeness only makes sense insofar as Δ_{max} captures a significant share of edges. In the worst case scenario, the random layout, Δ never captures more edges than if they were rewired at random (by definition). Technically, we could compute Δ_{max} and C_{max}, but C_{max} would be quasi-null and Δ_{max} would be degenerate. For that reason, as a protection against misuses, I recommend only displaying Δ_{max} if C_{max} is above 10%. Else, it is declared not applicable (figure 6).

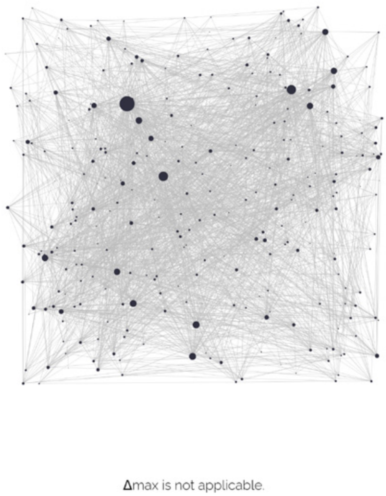


Figure 6: C. Elegans, random layout, visualized using Δ_{max}. As C_{max} is below 10%, Δ_{max} is declared non-applicable.

6 Implementation

6.1 Degenerate cases

Certain realizations of $C(\Delta)$ have a plateau on top, which makes finding C_{max} problematic (figure 7). We can use the smallest Δ as a tie-breaker, as smaller distance are more informative (more selective). However, in certain cases, the plateau has fluctuations and the solution is degenerate.

I propose, as a simple solution, to use a tolerance parameter ϵ. The formula is adapted to allow picking the smallest distance that fits the maximum of $C(\Delta)$ *with a tolerance of* ϵ. I use a reference value of $\epsilon = 0.03$ (i.e. 3%).

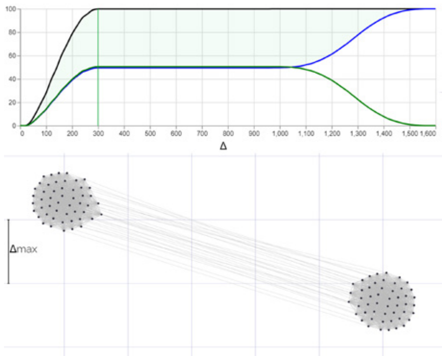


Figure 7: A planted partition model with $P_{in} = 99\%$. Layout: Force Atlas 2. The function $C(\Delta)$ (green) has a plateau, corresponding to the gap between the two clusters. The smallest distance is preferred, as it is the most informative.

6.2 Optimization

The steps of a naive implementation are:

- Compute all the distances between pairs of nodes
- Sample the distances
- Compute indicators for each distance
- Pick the max of $C(\Delta)$ to define Δ_{max} and relevant indicators

Computing and storing the distances between all node pairs is expensive. Then the sampling of distances is relatively straightforward, for instance using regular intervals up to the longest distance between node pairs. Yet if the network is sparse, the necessary precision may require small intervals. Both aspects can be optimized.

The distribution of $E_{\%}(\Delta)$ and $p_{\%}(\Delta)$ can be estimated by a simple random sampling of node pairs. I found a 10% sampling satisfying and lower percentages remained acceptable. As the curve itself is less important than its average, the errors on C_{max} and Δ_{max} are lower than the average error on $C(\Delta)$. But there is another easy improvement: add the list of edges to the sampling. Indeed, many networks are sparse and edge lengths need to be computed anyways. To keep it simple, I propose to sample as many pairs as there are edges. In the case of C. Elegans, it means a sampling of 2.7% node pairs, which leads to an error of 3.7% on C_{max} and 3.3% on Δ_{max}.

Finding C_{max} can be optimized by a grid search strategy. We split the range of distances in a number of equal parts, and we pick the part that is the most promising. Here, where $C(\Delta)$ is the highest. Then we iterate until the precision is satisfying. We leverage here the empirical observation that $C(\Delta)$ is a relatively smooth curve. The steps are as follows:

- Initialize the search with a range from 0 to the largest distance Δ, and set a grid size s.
- Compute $C(\Delta)$ in s equally separated distances across the whole range
- Pick the highest $C(\Delta)$ among the data points, and redefine the range from the previous to the next data point
- Iterate until the C_{max} is not improved significantly (or at all)

A reference implementation of this optimized algorithm is available online in a public Javascript notebook[1].

7 Benchmark (highlights)

I conducted a benchmark on connected-closeness using 14 network generators (e.g. stochastic bloc models) and 7 node-placement algorithms available in Javascript libraries (Javascript is popular for online data visualizations). For each *(generator, layout)* pair I generated and visualized 100 networks of 100 nodes, and computed the main indicators on the resulting layout: Δ_{max}, C_{max}, $E_{\%}(\Delta_{max})$, $p_{\%}(\Delta_{max})$, and $P_{edge}(\Delta_{max})$. The benchmark data and visualizations are detailed in an appendix. Here I only highlight the main takeaways.

Connected-closeness is a very stable metric. Force-directed placement algorithms are non-deterministic, and resulting node coordinates have a high variance. Yet we know that the patterns produced (e.g. clusters, center-periphery relations) can be stable. Connected-closeness captures this aspect very well.

Perhaps not so surprisingly, the C_{max} of a same network with a community structure (e.g. two cliques linked by a bridge) visualized by a force-directed layout (e.g. LinLog) has a standard variation as low as 0.0000819 for mean C_{max} of 50.5%.

More surprisingly, C_{max} is also stable for different networks with similar properties. For instance a stochastic bloc model with two blocs, an internal link probability of 80% and an external link probability of 20%. 100 different networks rendered with LinLog give an average C_{max} of 29.7% with a standard deviation of 0.00819. The benchmark shows consistently similar results for other network models and other force-directed layout algorithms.

Force-directed layouts do great in the presence of a community structure. This is expected considering that, as Noack wrote, "Modularity clustering is force-directed layout". Connected-closeness confirms it: C_{max} is consistently high for such networks (figure 8).

[1] `https://observablehq.com/@jacomyma/efficient-implementation-of-connected-close`

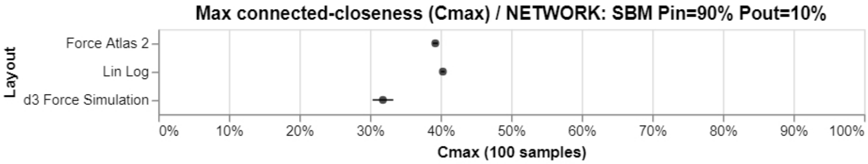


Figure 8: C_{max} for 100 renditions of a stochastic bloc model with $P_{in} = 90\%$ and $P_{out} = 10\%$, for three different force-directed layouts. The dots represent the average, the error bars the standard deviation.

As the community structure decreases, so does connected-closeness. A stochastic block model allows quantifying the influence of the community structure (figure 9). As the internal link probability P_{in} drops closer to 50%, the community structure disappears. C_{max} drops accordingly (figure 10).

Connected-closeness is low for random layouts. As expected. Indeed, by definition they do not even try to bring connected nodes closer; they put all nodes randomly close regardless of whether or not they are connected. Their connected closeness is close to zero (figure 11).

In the same perspective, "bad" layouts perform worse than "good" layouts on the same network. The benchmark features a "bad" parametrization of Force Atlas 2: the strong gravity and the low resolution of the simulation introduce randomness, and the layout is stopped after too few steps. The resulting layouts are visibly glitchy (figure 12). Following intuition, this layout performs half-way between the default settings of Force Atlas 2, and a random layout (figure **??**). Remark that even for bad and random layouts, the standard deviation of C_{max} is very low.

Force-directed layouts perform better on sparse networks. Bringing connected nodes closer is less constrained in networks with a low density. Force-directed algorithms are very good at producing a high C_{max} in this context (figures 14 and 15).

Layouts are pointless on cliques. This follows intuition: as every node is connected to every other node, all are topologically equivalent, and the node placement is meaningless unless all nodes are stacked on the same coordinates. By definition C_{max} is always null for cliques, as rewiring edges makes no difference whatsoever. The same argument is true for stables (networks with no links).

The denser the network, the lower C_{max} is achieved by force-directed layouts. This intuitively follows the case of cliques. We can see it experimentally by comparing random networks with different densities (figure 16).

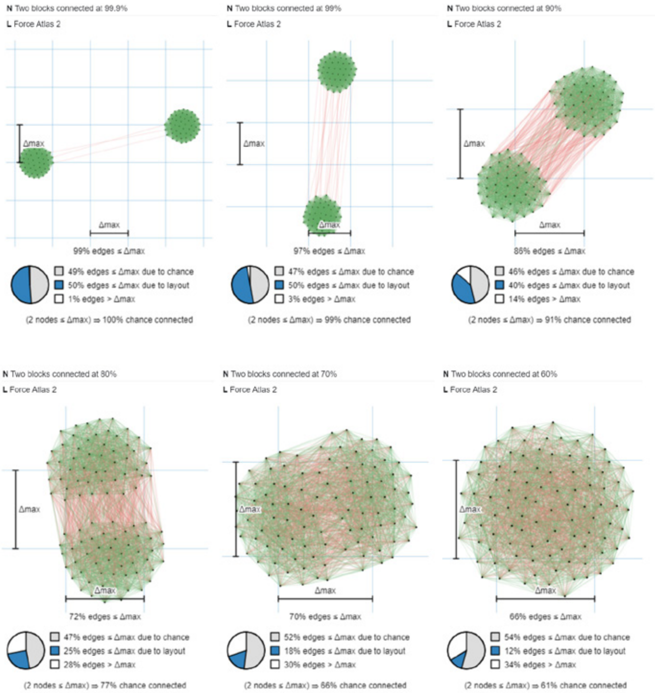


Figure 9: Samples of stochastic bloc model networks with a decreasing community structure. Layout: Force Atlas 2. P_{in} in reading order: 99.9%; 99%; 90%; 80%, 70% and 60%.

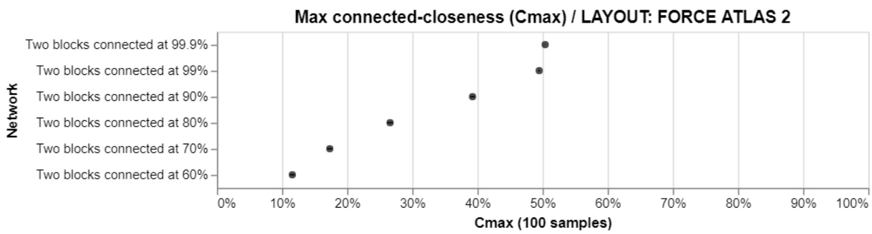


Figure 10: C_{max} for 100 renditions of stochastic bloc models with decreasing P_{in}. Layout: Force Atlas 2. The dots represent the average, the error bars the standard deviation.

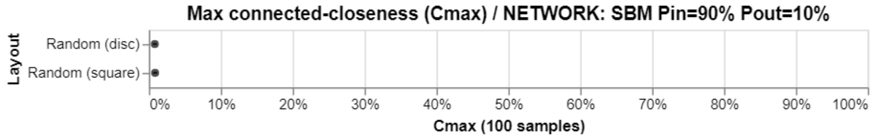


Figure 11: C_{max} for 100 renditions of a network with a community structure with random layouts. The dots represent the average, the error bars the standard deviation.

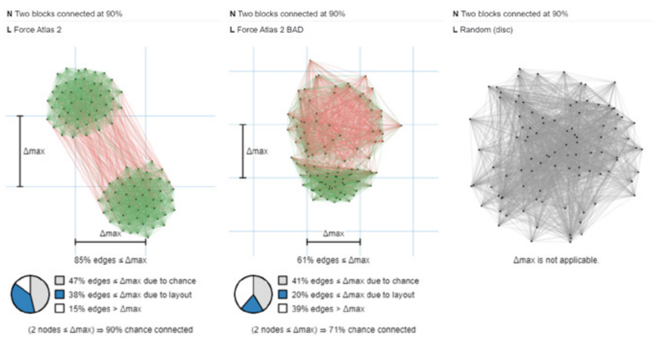


Figure 12: The same network with a community structure, rendered with three layouts. Left to right: Force Atlas 2 with default settings, Force Atlas 2 with intentionally bad settings, random layout.

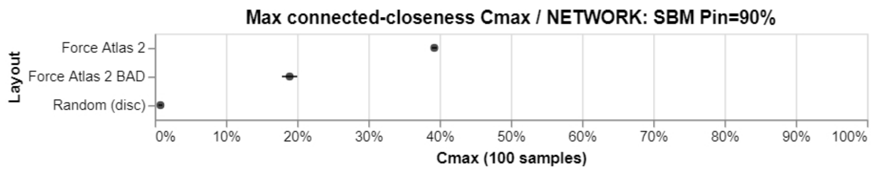


Figure 13: C_{max} for 100 renditions of a network with a community structure with three layouts, from “good” to “bad”. The dots represent the average, the error bars the standard deviation.

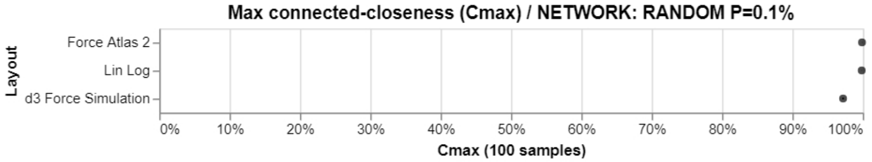


Figure 14: C_{max} for 100 renditions of a sparse random network (link probability 0.1%) with three different force-directed networks. The dots represent the average, the error bars the standard deviation.

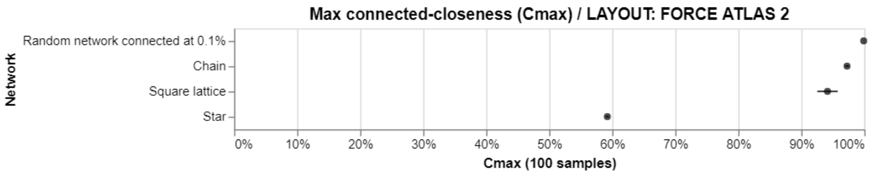


Figure 15: C_{max} for 100 renditions of a chain network with three different force-directed networks. The dots represent the average, the error bars the standard deviation.

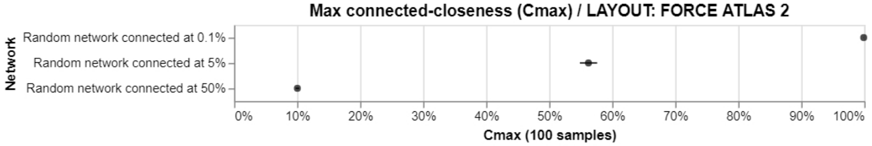


Figure 16: C_{max} for 100 renditions of a random networks with three different densities. Layout: Force Atlas 2. The dots represent the average, the error bars the standard deviation.

8 Conclusion

In this paper I presented connected-closeness, a metric consisting of two distinct parts: the maximal connected-closeness $C_{max} = C(\Delta_{max})$, and the distance of maximal connected-closeness Δ_{max}. Δ_{max} is characteristic of the layout, and is intended to be drawn on the visualization as a contextual element. C_{max} is characteristic of both the network and the layout, and is only high when, intuitively, the distances in the layout can be interpreted meaningfully.

In practice, as the benchmark illustrates, connected-closeness offers us different opportunities:

1. It allows formulating a quantitative statement about the placement of nodes in the visualization. The simplest statement is of the following kind: "76% of connected nodes are Δ_{max} or closer." Since Δ_{max} is represented on the picture, it provides contextual information on the relation between the topology (connectedness) and its representation (closeness).

2. Maximal connected-closeness C_{max} validates the layout. Different layouts have different goals, and this metric only accounts for one of them (bringing connected nodes closer). It tells you a game at which the layout is supposedly good, and check that it actually is. The benchmark shows that force-directed layouts are indeed good at the game of bringing connected nodes closer, but also detects situations and layouts that are bad at it.

3. It allows comparability. As C_{max} is comparable on different layouts for a given network, it can be used as a layout quality metric to determine which algorithm performs better. Optimization aside, the metric is deterministic and the benchmark has shown that its standard variation is, in most situations, very low.

4. It shows that layouts capture something of the topological structure of networks. Force-driven placement algorithms are non-deterministic. It means that from one time to another you run them, they do not provide the same result. One might conclude that they are not reliable. Practice tells otherwise, but it is not easy to quantify how similar are two renderings of the same network, by the same layout algorithm, while all node positions are different. Maximal connected-closeness, as a highly consistent measure of network layouts, proves that some of them (e.g. force-directed algorithms) consistently capture an aspect of the topological structure of the network they represent.

References

A Appendix: Benchmark (details)

I conducted a benchmark on connected-closeness. I used 14 network generators (e.g. stochastic bloc models) and 7 node-placement algorithms available in Javascript. The choice of Javascript is justified by its importance for interactive data visualizations. One of the algorithms used is the default choice offered by the *D3.js* library. For each *(generator, layout)* pair I generated and visualized 100 networks of 100 nodes, and computed the main indicators on the resulting layout: Δ_{max}, C_{max}, $E_{\%}(\Delta_{max})$, $p_{\%}(\Delta_{max})$, and $P_{edge}(\Delta_{max})$. The benchmark is available as an online notebook[2], as well as its analysis, including the data[3].

Network generators. 14 different strategies were used to generate networks. Note that some of them generate a different network every time (e.g. random network) and others do not (e.g. clique).

- **Clique.** All nodes are connected.
- **Two bridged cliques.** 2 cliques (groups of fully connected nodes) connected by 1 edge.
- **Two blocks connected at 99.9%.** Network generated by stochastic block model. It has 2 blocks. Two nodes in the same block have a 99.9% probability of being connected. Two nodes in a different block have a 0.1% probability of being connected.
- **Two blocks connected at 99%.** Network generated by stochastic block model. It has 2 blocks. Two nodes in the same block have a 99% probability of being connected. Two nodes in a different block have a 1% probability of being connected.
- **Two blocks connected at 90%.** Network generated by stochastic block model. It has 2 blocks. Two nodes in the same block have a 90% probability of being connected. Two nodes in a different block have a 10% probability of being connected.
- **Two blocks connected at 80%.** Network generated by stochastic block model. It has 2 blocks. Two nodes in the same block have a 80% probability of being connected. Two nodes in a different block have a 20% probability of being connected.
- **Two blocks connected at 70%.** Network generated by stochastic block model. It has 2 blocks. Two nodes in the same block have a 70% probability of being connected. Two nodes in a different block have a 30% probability of being connected.

[2]https://observablehq.com/@jacomyma/evaluating-the-connected-closeness-metric-p
[3]https://observablehq.com/@jacomyma/highlights-on-connected-closeness

- **Two blocks connected at 60%.** Network generated by stochastic block model. It has 2 blocks. Two nodes in the same block have a 60% probability of being connected. Two nodes in a different block have a 40% probability of being connected.
- **Random network connected at 50%.** Random network: two nodes have a 50% probability of being connected.
- **Random network connected at 5%.** Random network: two nodes have a 5% probability of being connected.
- **Random network connected at 0.1%.** Random network: two nodes have a 0.1% probability of being connected.
- **Chain.** A chain of nodes.
- **Star.** Network with a central node, and the other nodes are only connected to that one.
- **Square lattice.** This network is a square grid of nodes.

Layouts. 7 different algorithms were used to generate networks.

- **Force Atlas 2.** The Force Atlas 2 layout with standard settings.
- **Force Atlas 2 BAD.** The Force Atlas 2 layout with bad settings: too much gravity, not enough iterations.
- **Lin Log.** The Force Atlas 2 layout with the *LinLog* energy model.
- **Random (in a disc).** Nodes are placed at random in a disc.
- **Random (Graphology).** Nodes are placed at random in a square, using the method from the Graphology library.
- **Circular layout.** Nodes are placed around a circle. Uses the method from the Graphology library. Note: this algorithm uses the order of nodes. For most generators (bridged cliques, bloc models, chain, star and lattice) the nodes are ordered in a relevant way, which produces remarkable patterns. For the random network generators, the node order is irrelevant and the circular layout will behave similarly to a random layout.
- **D3 Force Simulation.** The force-directed layout algorithm implemented in the library *D3.js*, with default settings.

A.1 Visual examples

You will find here one rendition for each $(networkgenerator, layout)$ pair. For each of these 14×7 cases, the rendered network is visualized and accompanied by a plot. The network visualization has colored edges if $C_{max} > 10\%$, with edges shorter than Δ_{max} in green, and longer edges in red. The plot features the main indicators over the Euclidean distance Δ. The share of edges shorter than Δ, $E_{\%}(\Delta)$, is plotted in black. The share of node pairs closer than Δ, $p_{\%}(\Delta)$, is plotted in blue. The connected-closeness $C(\Delta)$ is plotted in green. Its maximal point $C_{max} = C(\Delta_{max})$ is highlighted by a vertical green bar.

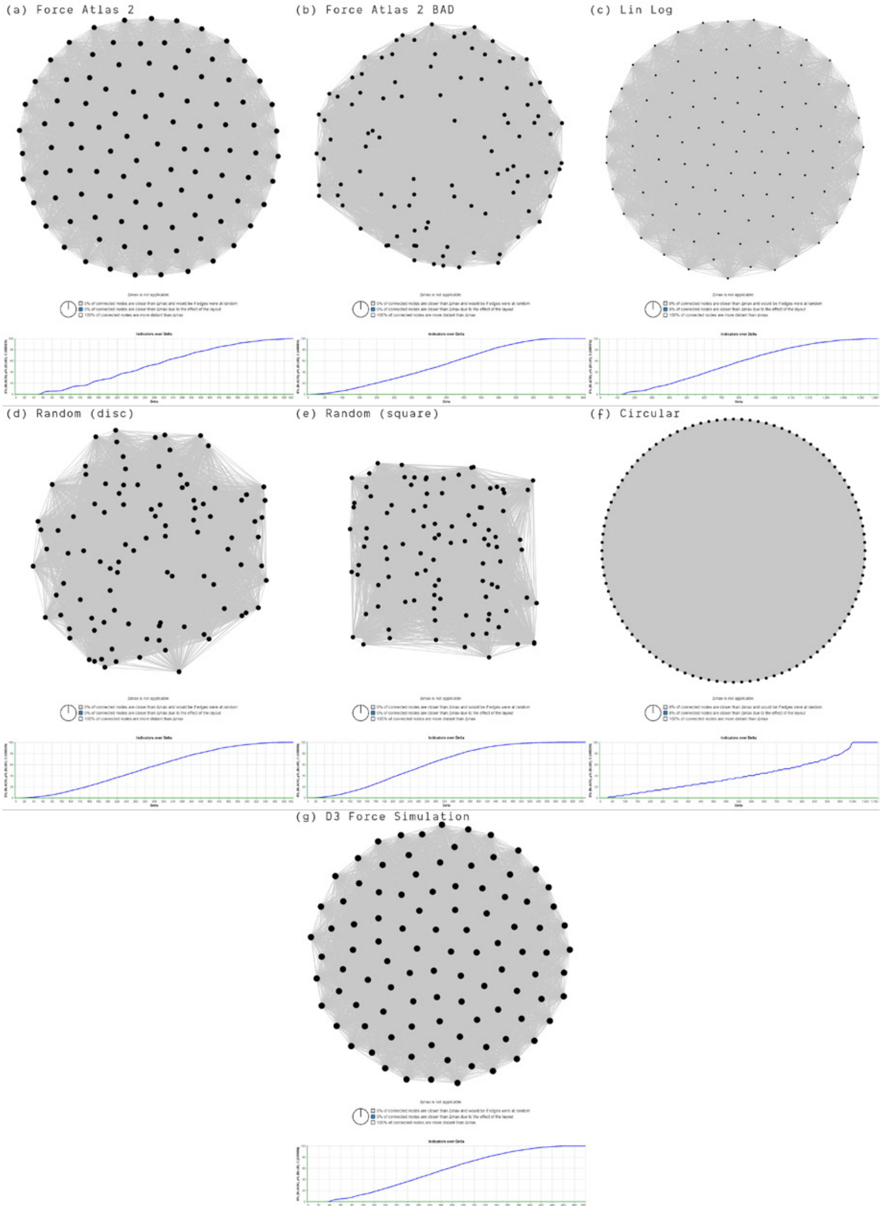


Figure 17: Clique

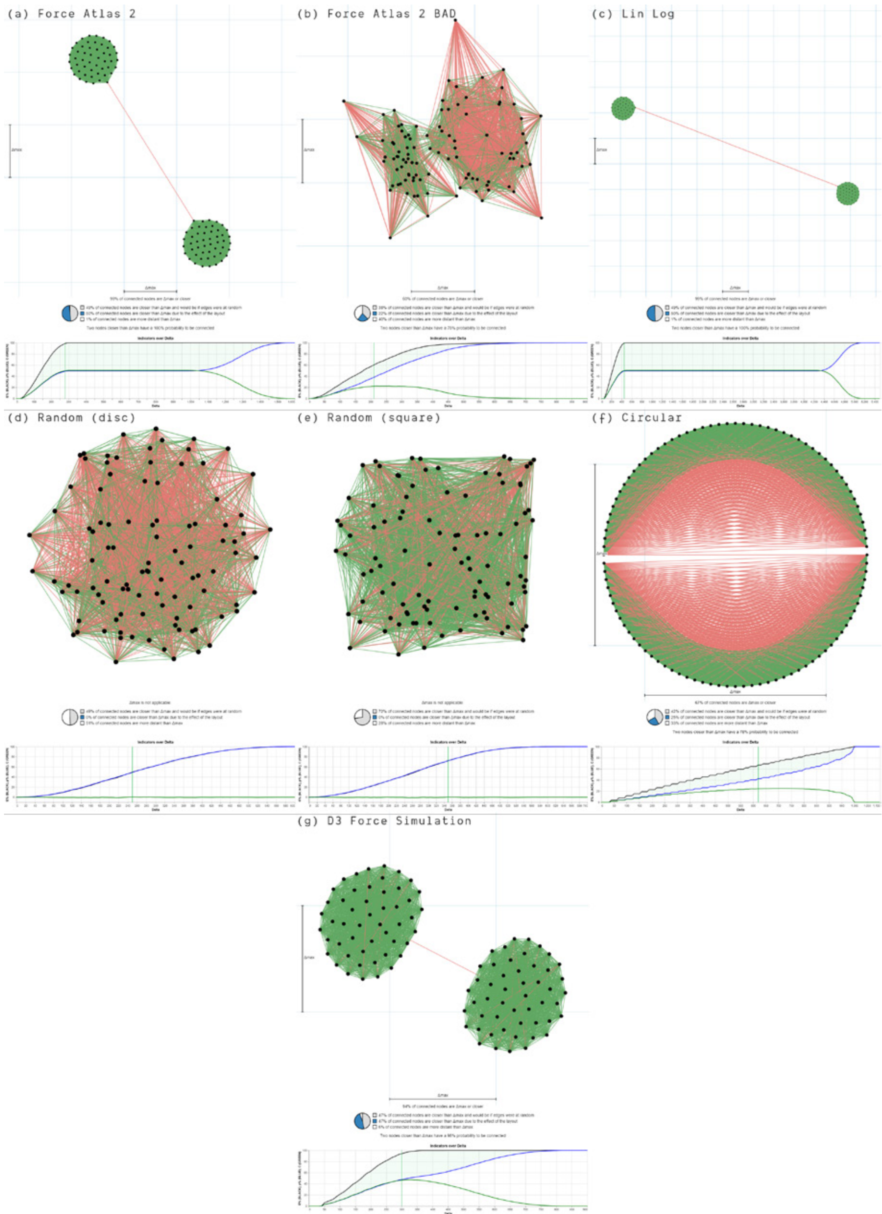


Figure 18: Two cliques connected by one bridge

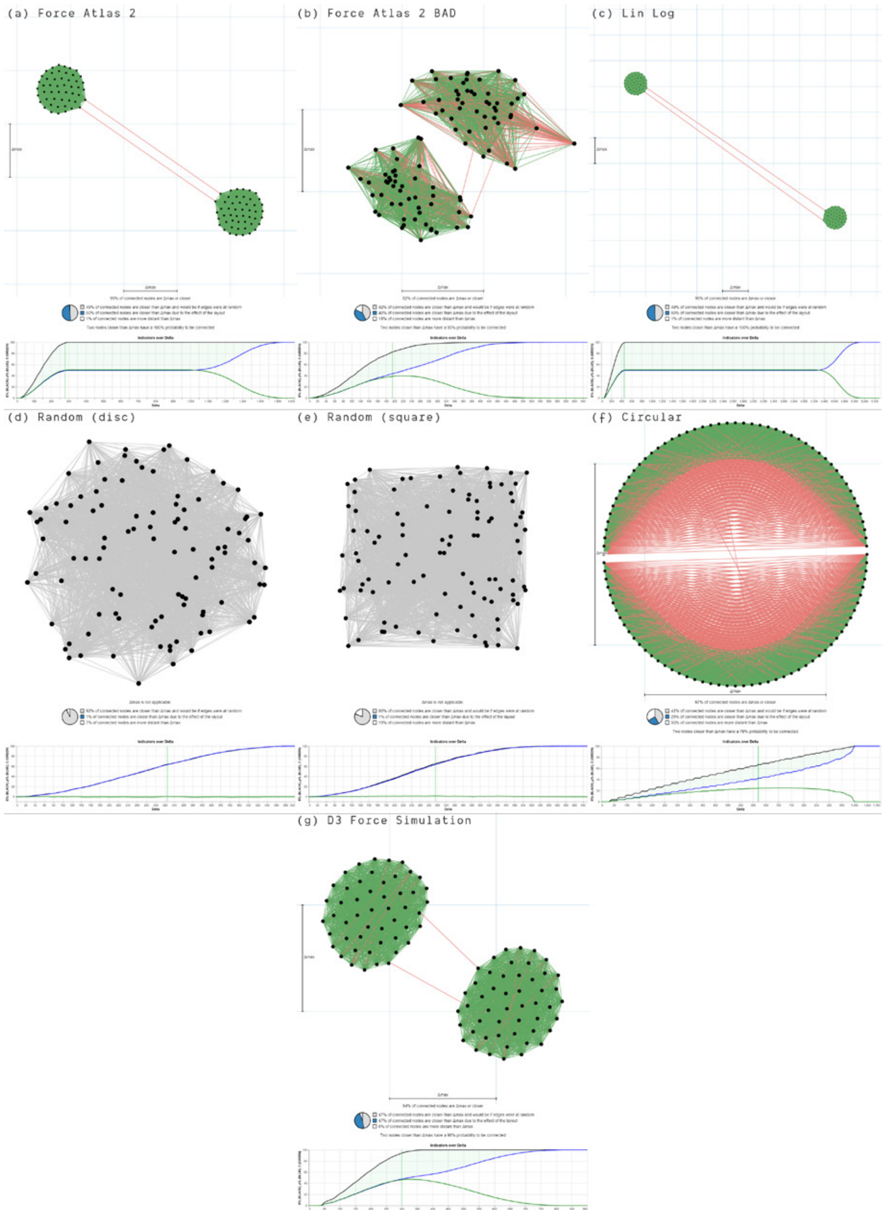


Figure 19: Two blocks internally connected with a probability of 99.9% (and 0.1% in-between)

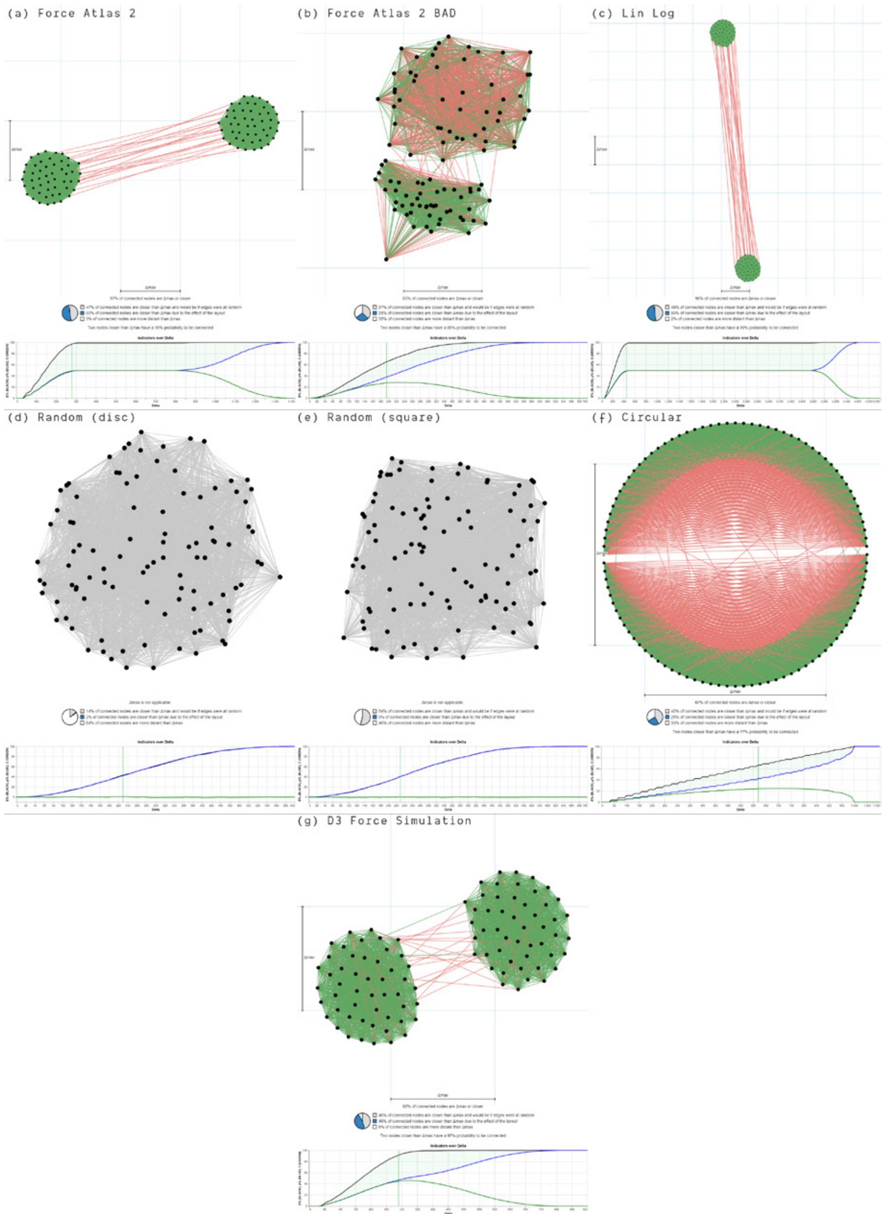


Figure 20: Two blocks internally connected with a probability of 99% (and 1% in-between)

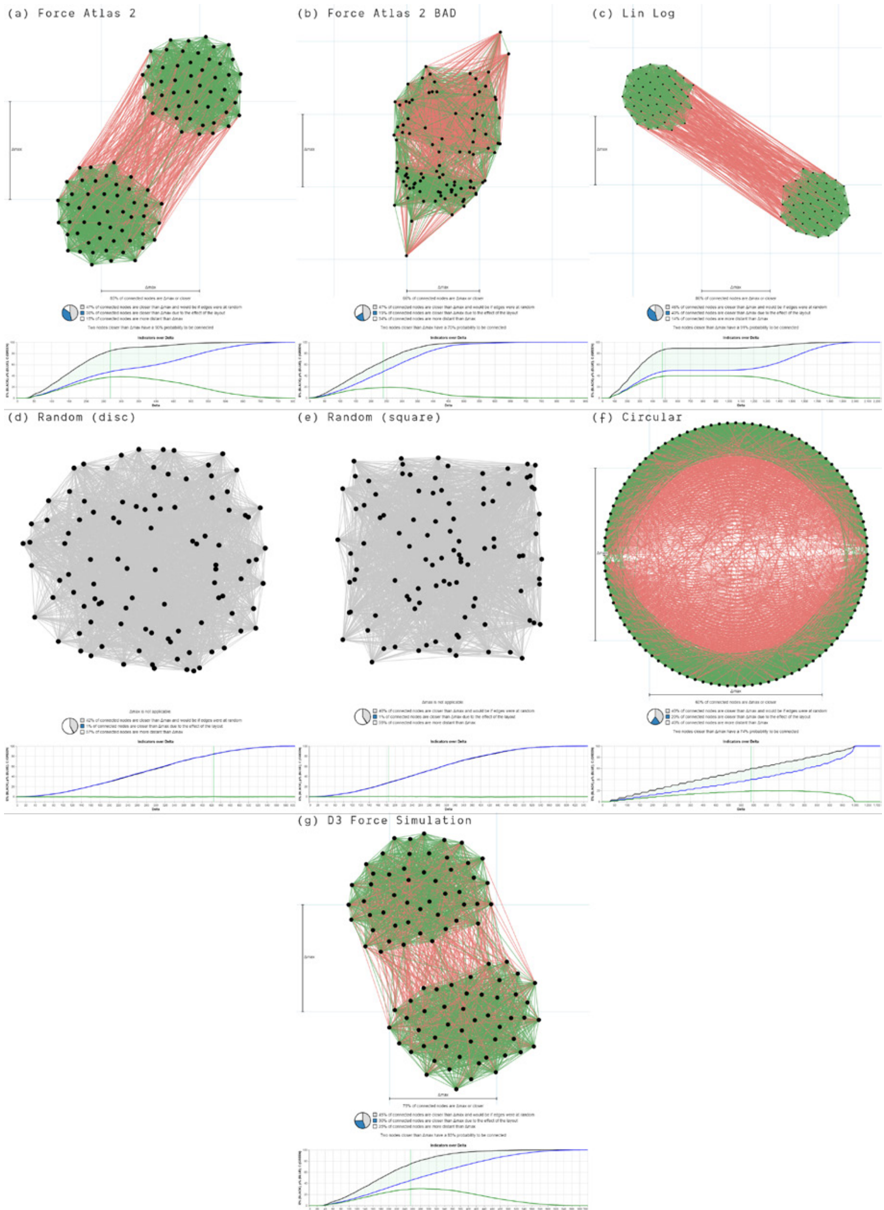


Figure 21: Two blocks internally connected with a probability of 90% (and 10% in-between)

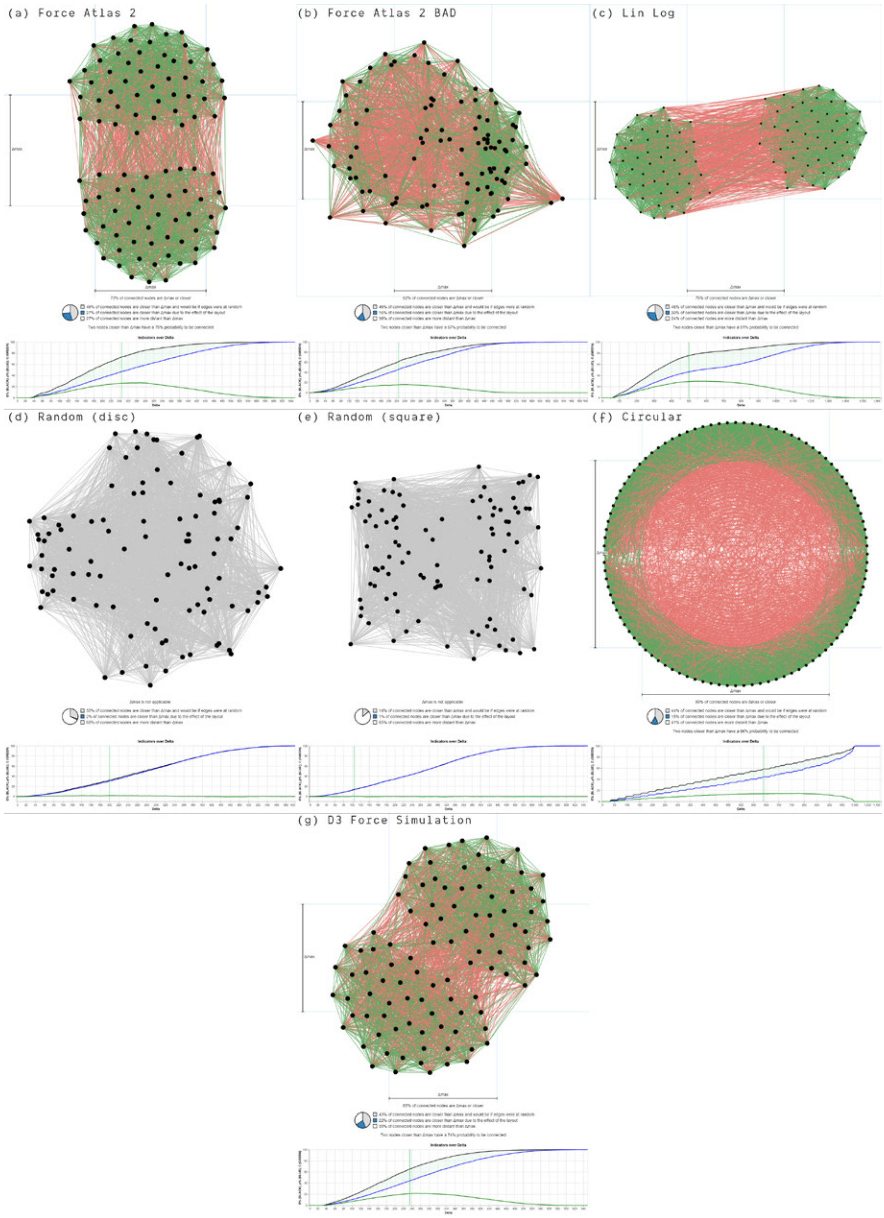


Figure 22: Two blocks internally connected with a probability of 80% (and 20% in-between)

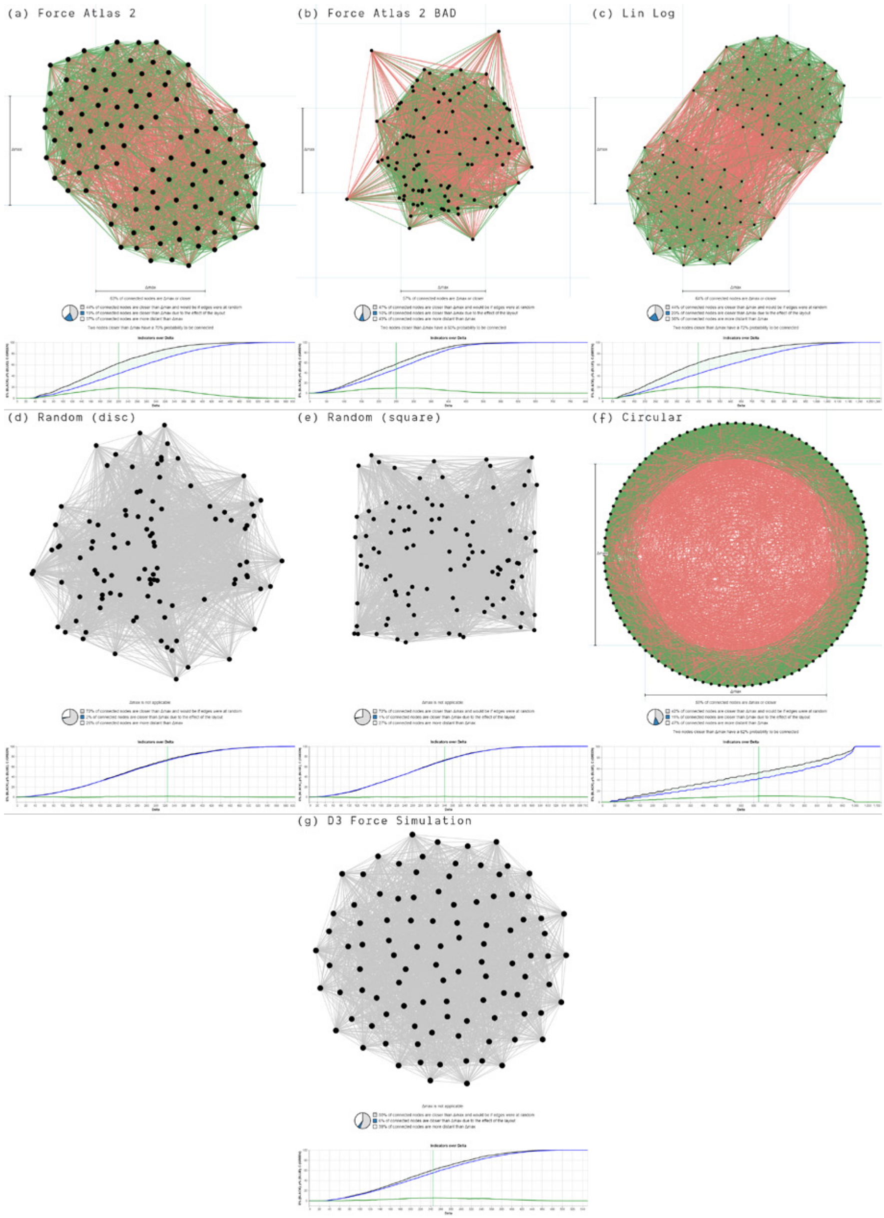


Figure 23: Two blocks internally connected with a probability of 70% (and 30% in-between)

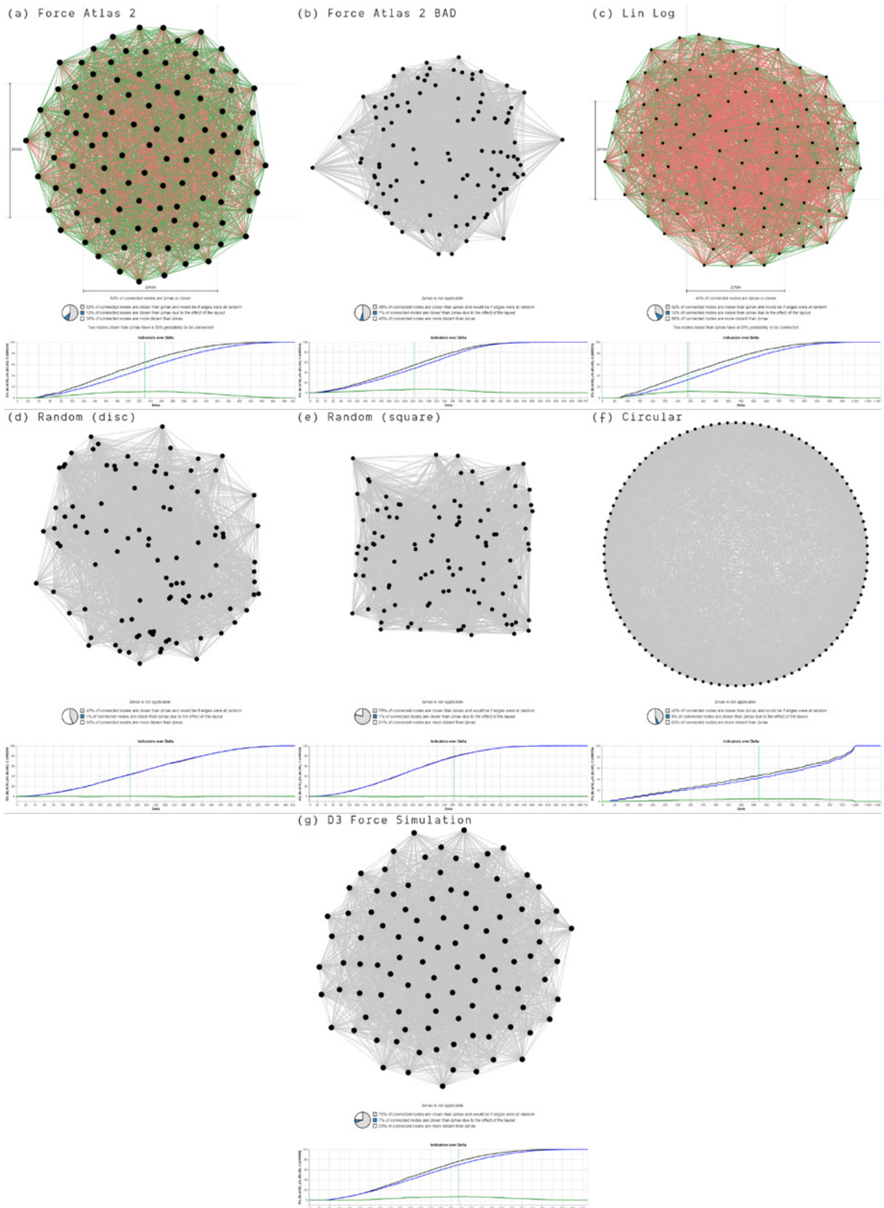


Figure 24: Two blocks internally connected with a probability of 60% (and 40% in-between)

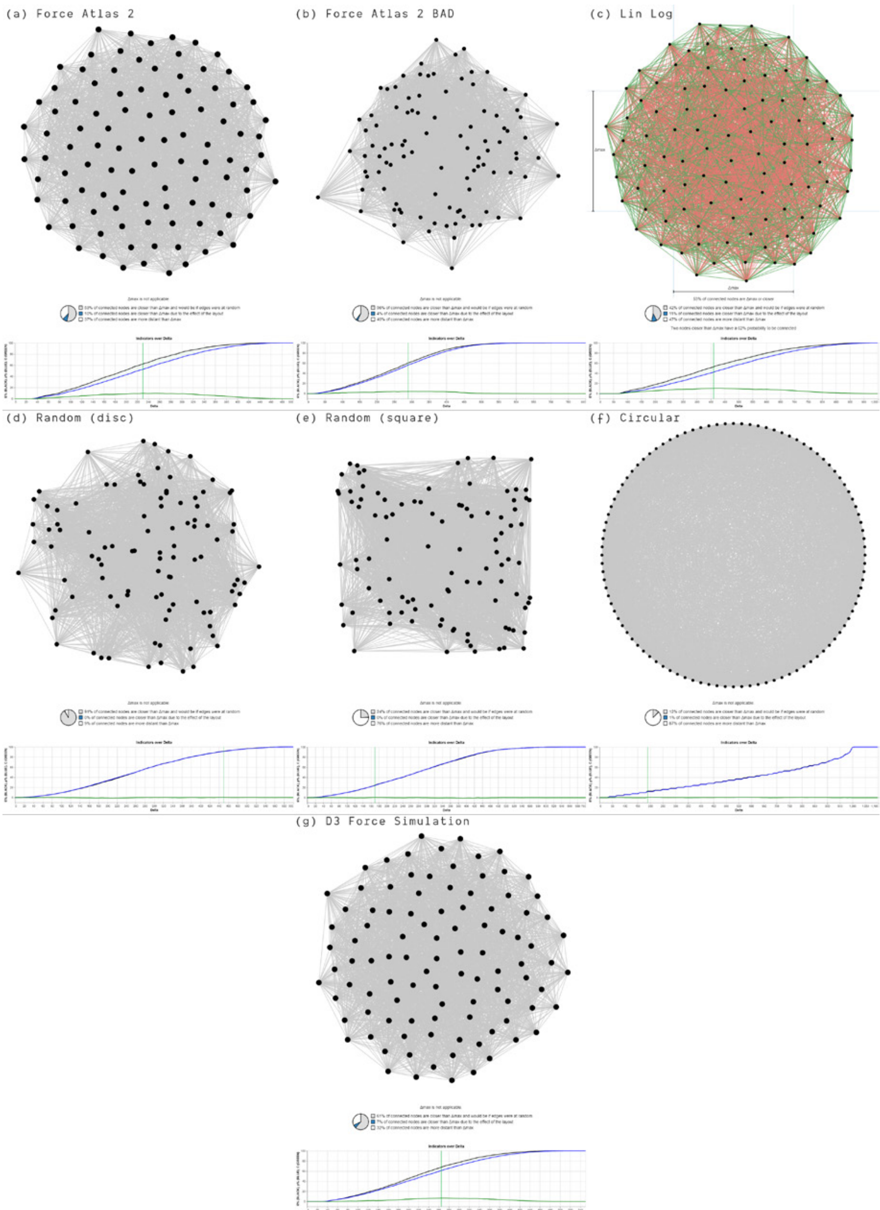


Figure 25: Random network with a connection probability of 50%

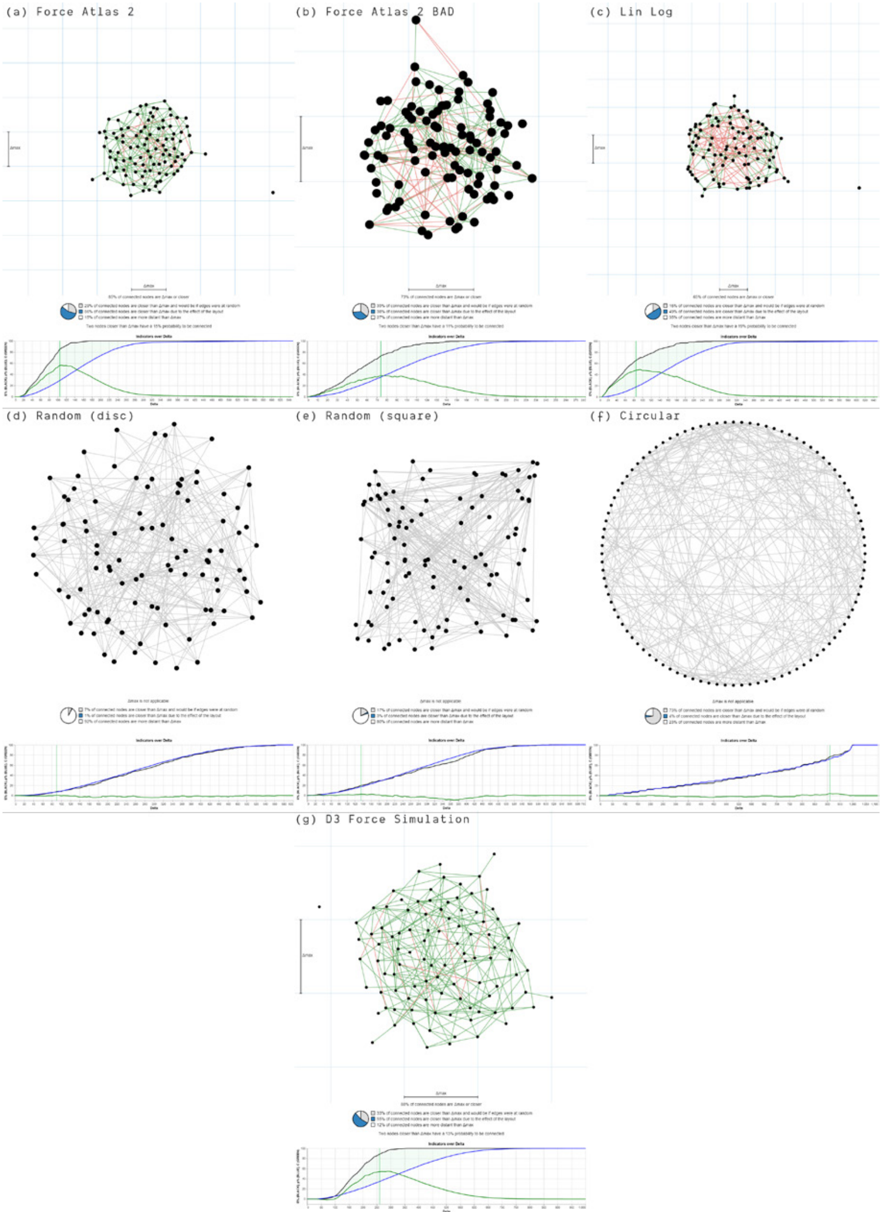


Figure 26: Random network with a connection probability of 5%

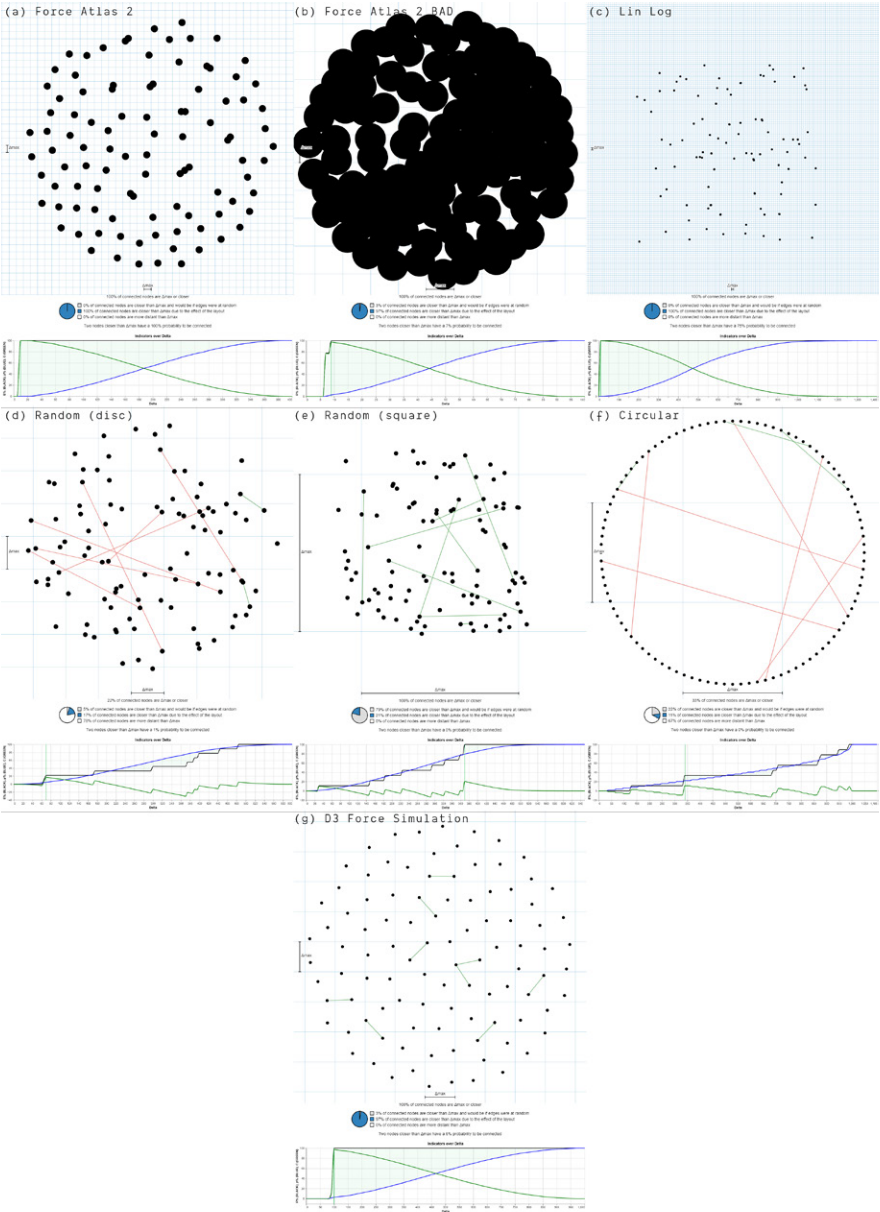


Figure 27: Random network with a connection probability of 0.1%

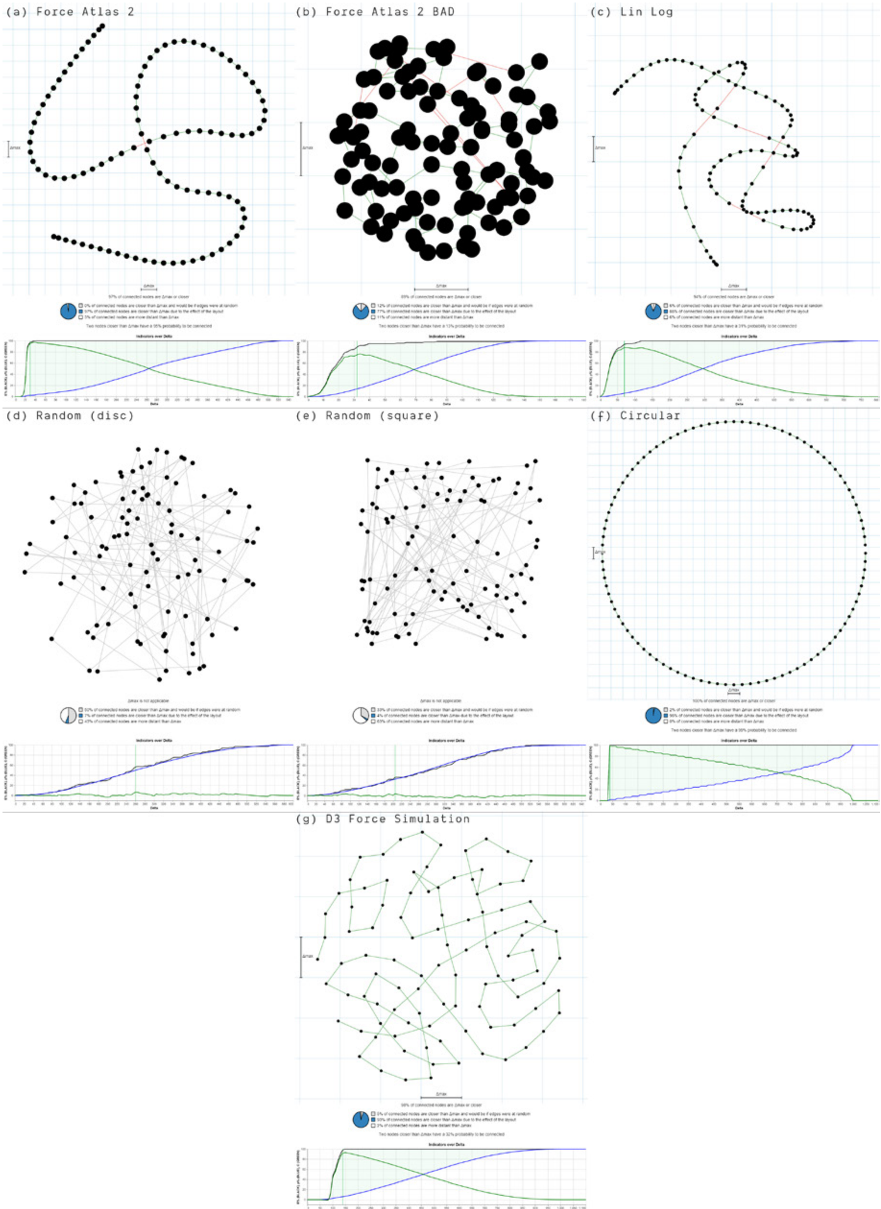


Figure 28: Chain

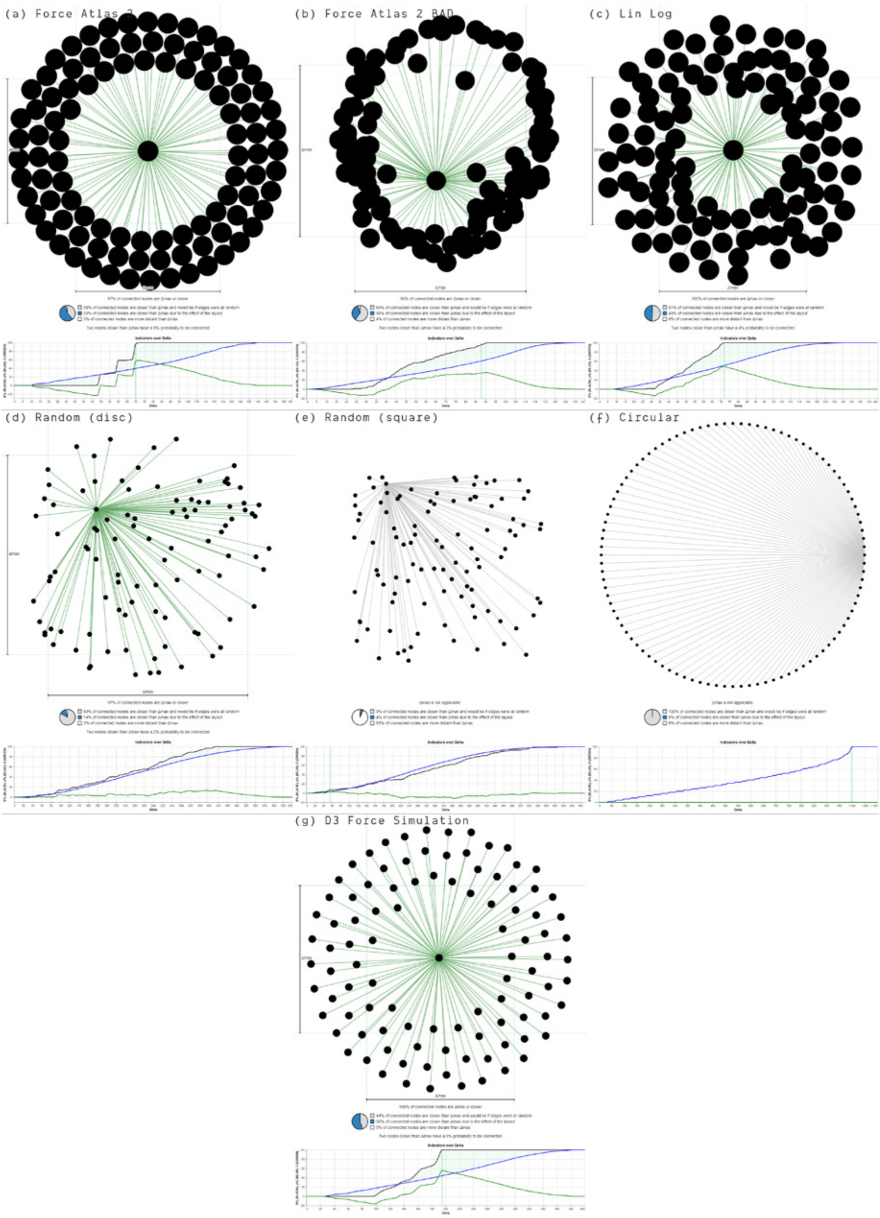


Figure 29: Star

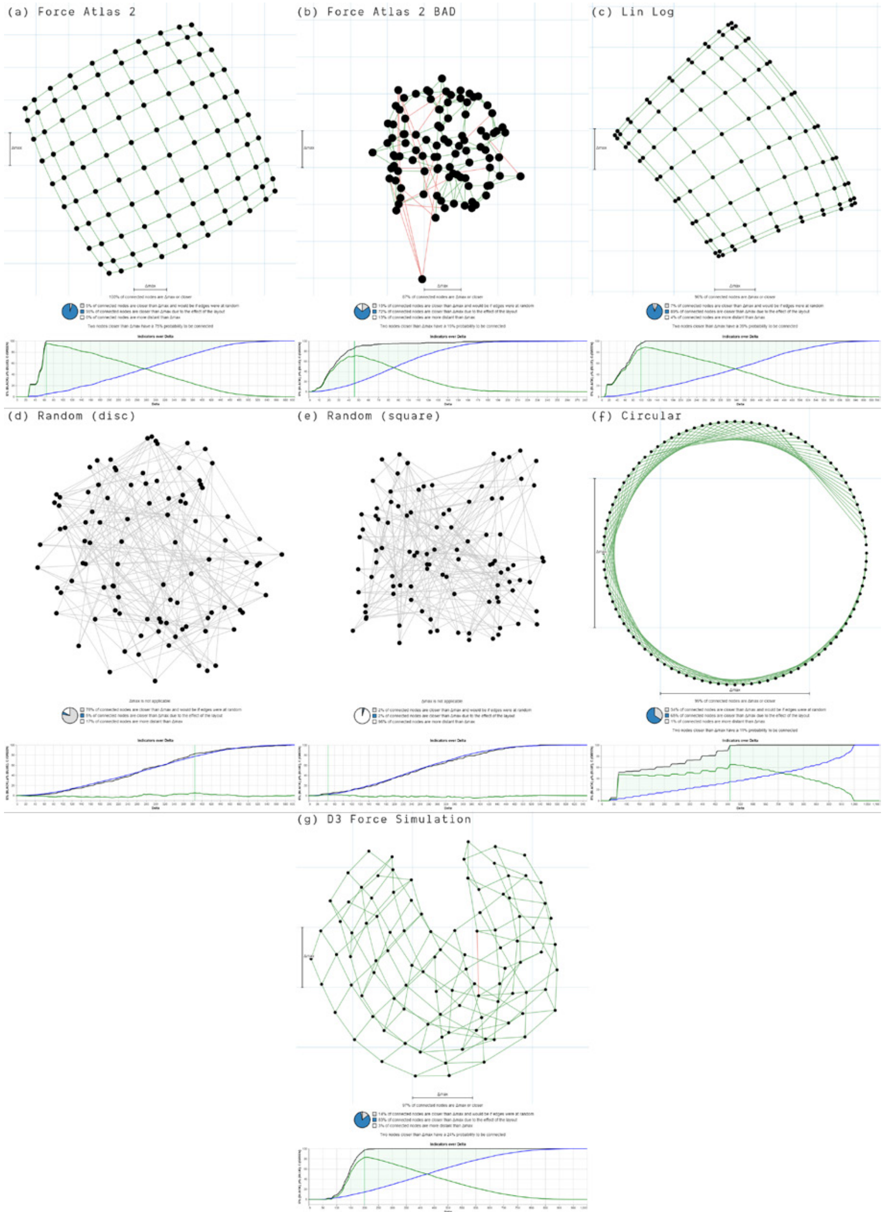
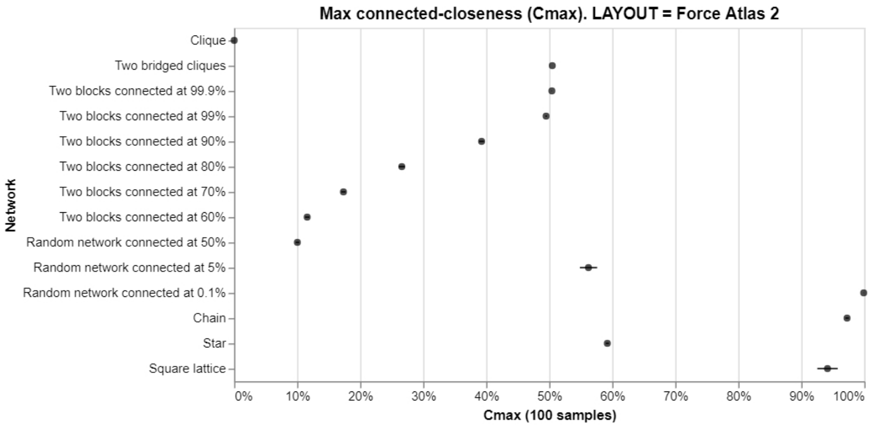


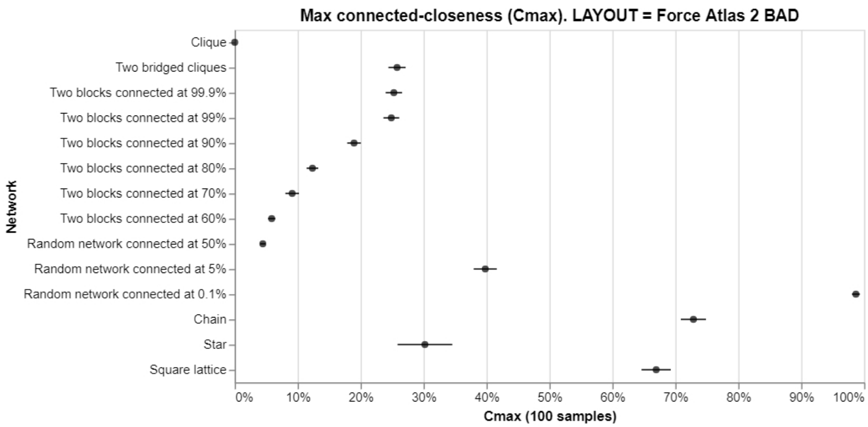
Figure 30: Square lattice

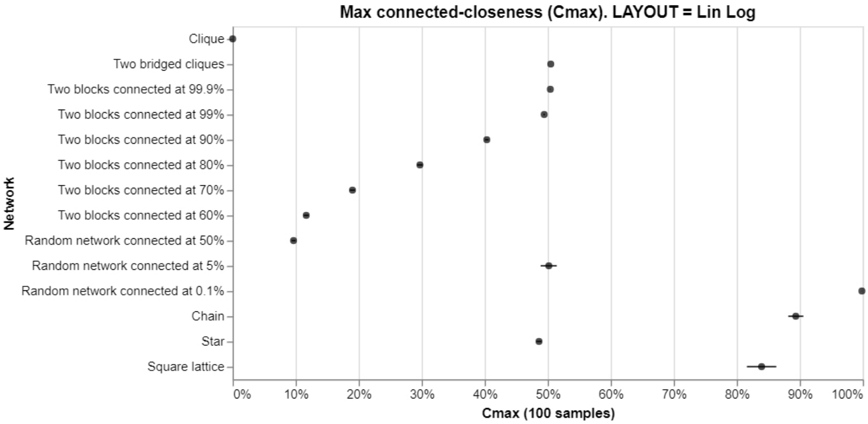
A.2 Maximum connected-closeness $C_{max} = C(\Delta_{max})$

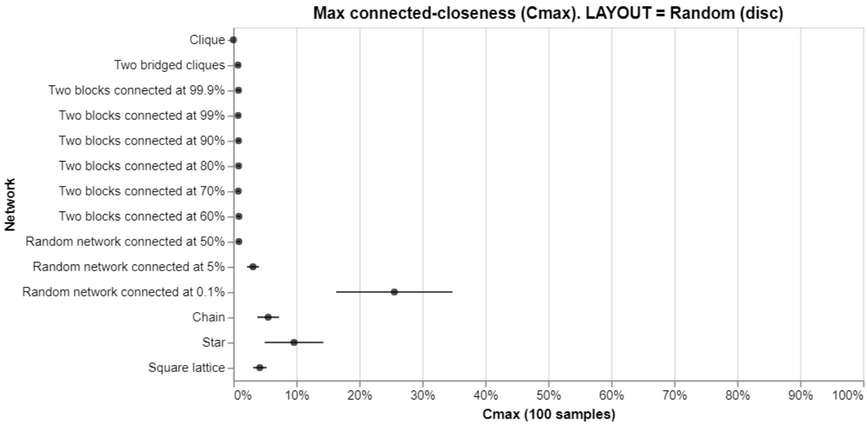
C_{max} is the maximal percentage of unexpectedly close connected nodes. For a given network, it allows comparing different layouts, and for a layout, it allows comparing different networks. Higher is better, as it means that the layout captures more unexpected edges under distance Δ_{max}.

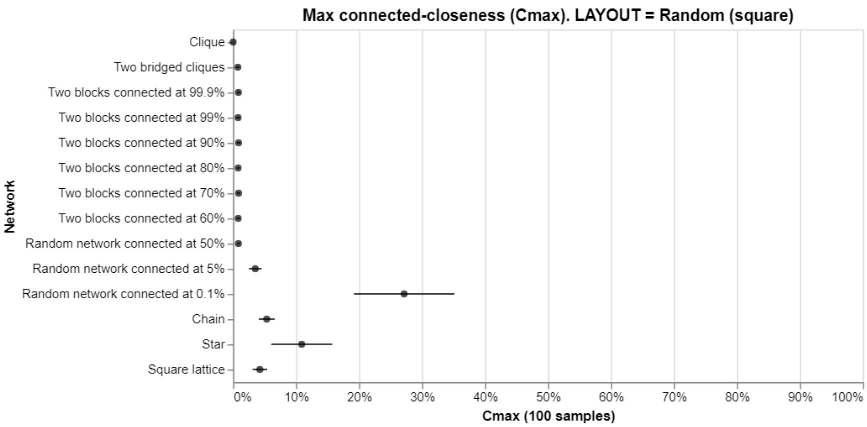
For each *(network generator, layout)* pair, the values for the 100 renditions are represented as a dot (mean) with an error bar (standard deviation).

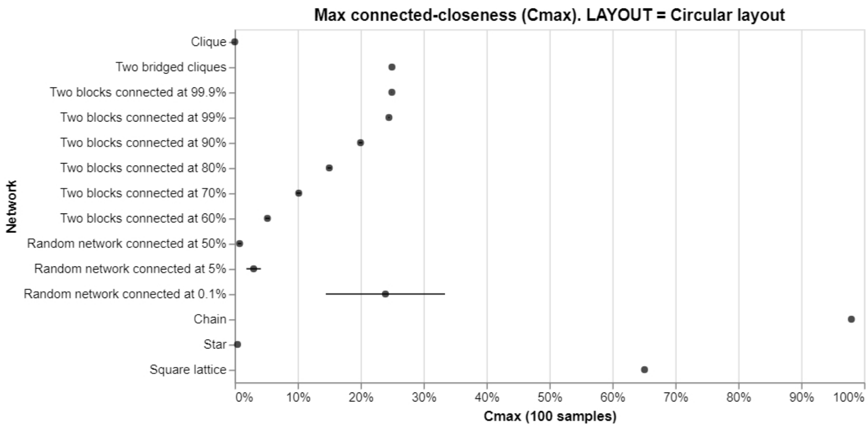


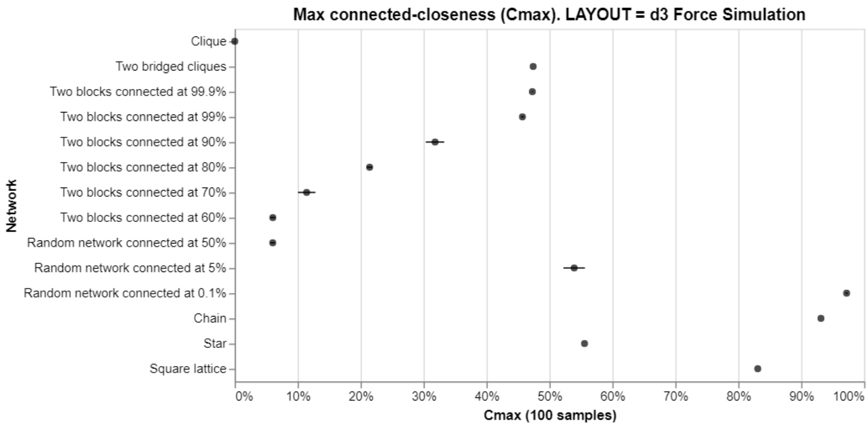



Max connected-closeness (Cmax). LAYOUT = Lin Log
Network
Clique
Two bridged cliques
Two blocks connected at 99.9%
Two blocks connected at 99%
Two blocks connected at 90%
Two blocks connected at 80%
Two blocks connected at 70%
Two blocks connected at 60%
Random network connected at 50%
Random network connected at 5%
Random network connected at 0.1%
Chain
Star
Square lattice
0% 10% 20% 30% 40% 50% 60% 70% 80% 90% 100%
Cmax (100 samples)


Max connected-closeness (Cmax). LAYOUT = Random (disc)
Network
Clique
Two bridged cliques
Two blocks connected at 99.9%
Two blocks connected at 99%
Two blocks connected at 90%
Two blocks connected at 80%
Two blocks connected at 70%
Two blocks connected at 60%
Random network connected at 50%
Random network connected at 5%
Random network connected at 0.1%
Chain
Star
Square lattice
0% 10% 20% 30% 40% 50% 60% 70% 80% 90% 100%
Cmax (100 samples)


Max connected-closeness (Cmax). LAYOUT = Random (square)
Network
Clique
Two bridged cliques
Two blocks connected at 99.9%
Two blocks connected at 99%
Two blocks connected at 90%
Two blocks connected at 80%
Two blocks connected at 70%
Two blocks connected at 60%
Random network connected at 50%
Random network connected at 5%
Random network connected at 0.1%
Chain
Star
Square lattice
0% 10% 20% 30% 40% 50% 60% 70% 80% 90% 100%
Cmax (100 samples)

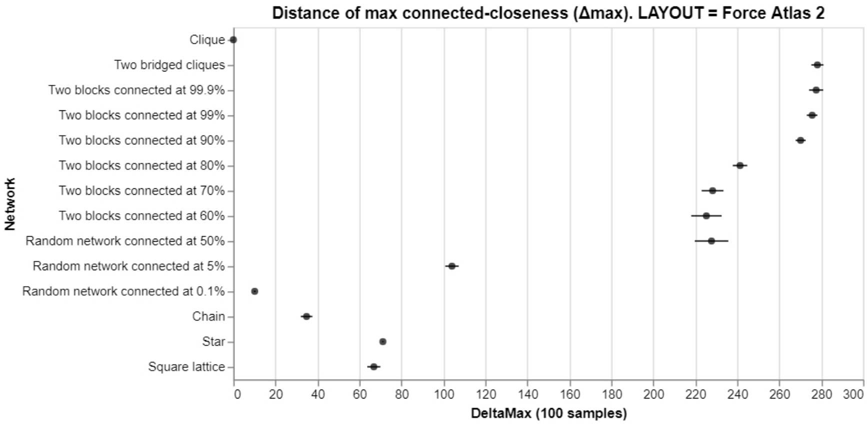

Max connected-closeness (Cmax). LAYOUT = Circular layout
Network
Clique
Two bridged cliques
Two blocks connected at 99.9%
Two blocks connected at 99%
Two blocks connected at 90%
Two blocks connected at 80%
Two blocks connected at 70%
Two blocks connected at 60%
Random network connected at 50%
Random network connected at 5%
Random network connected at 0.1%
Chain
Star
Square lattice
0% 10% 20% 30% 40% 50% 60% 70% 80% 90% 100%
Cmax (100 samples)

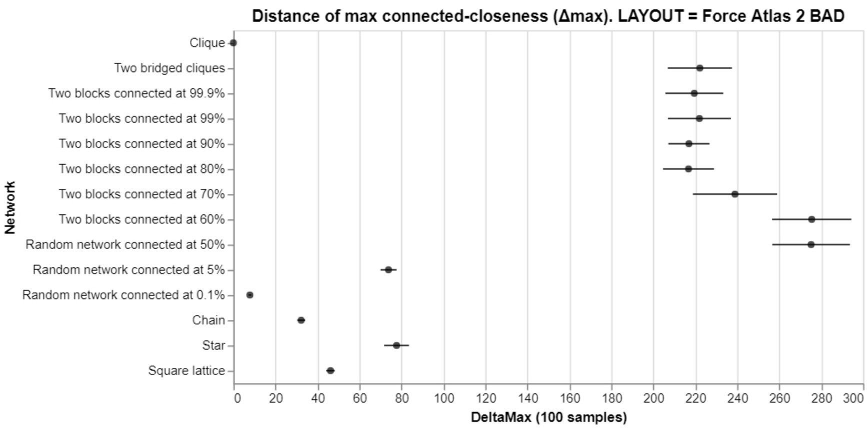

Max connected-closeness (Cmax). LAYOUT = d3 Force Simulation
Network
Clique
Two bridged cliques
Two blocks connected at 99.9%
Two blocks connected at 99%
Two blocks connected at 90%
Two blocks connected at 80%
Two blocks connected at 70%
Two blocks connected at 60%
Random network connected at 50%
Random network connected at 5%
Random network connected at 0.1%
Chain
Star
Square lattice
0% 10% 20% 30% 40% 50% 60% 70% 80% 90% 100%
Cmax (100 samples)

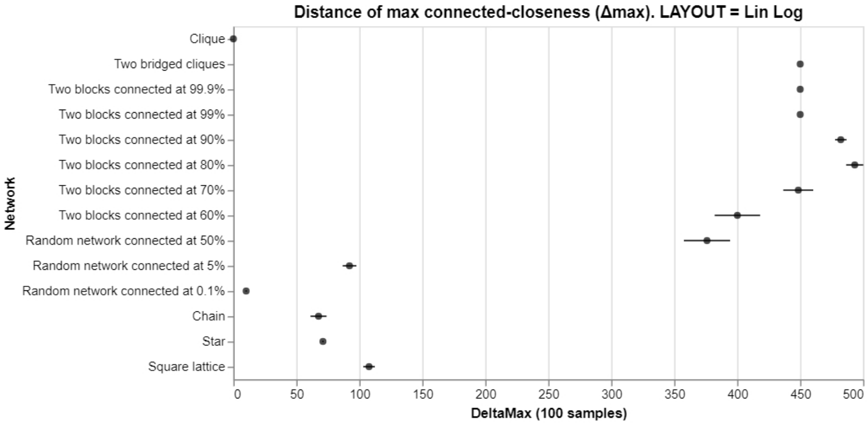
A.3 Distance of maximum connected-closeness Δ_{max}

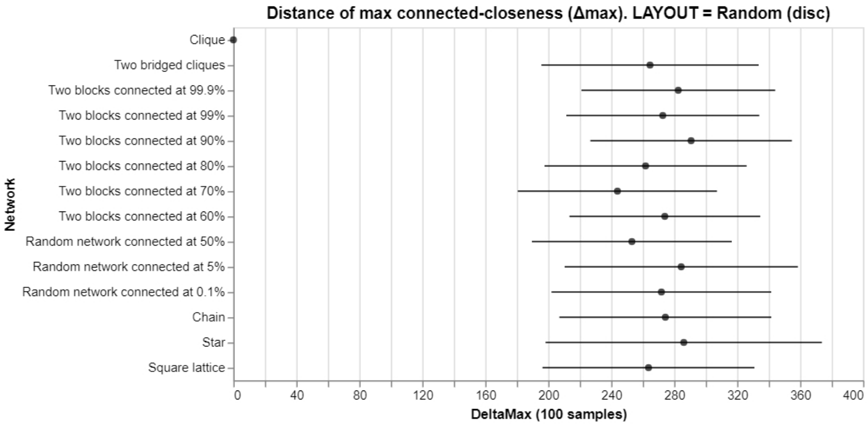
Δ_{max} is the Euclidean distance defining the maximal percentage of unexpectedly close connected nodes. Its unit is the arbitrary unit generated by the node coordinates provided by the layout (it is not normalized). For a given layout, it allows comparing different networks. It does not compare from one layout to another. Lower is better, but only insofar as $C(\Delta_{max})$ is high. Δ_{max} by itself does not tell much about a network map, as its purpose is to be drawn on the visualization to provide context. It is however useful to look at how if behaves in different situations, and notably its consistency (standard deviation).

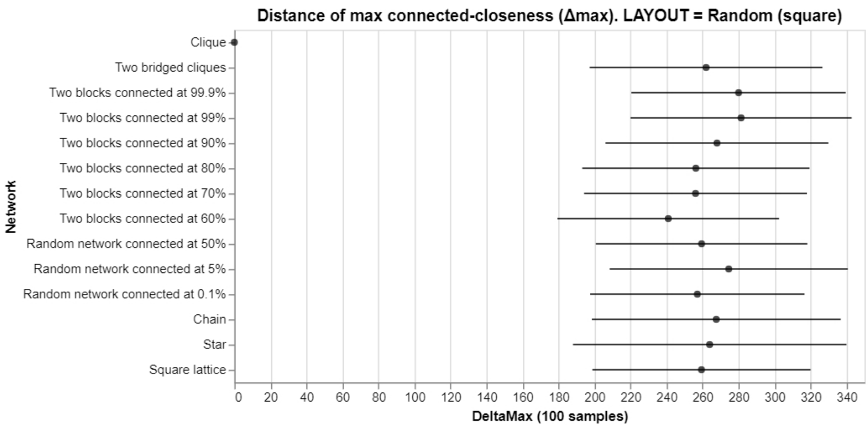
For each *(network generator, layout)* pair, the values for the 100 renditions are represented as a dot (mean) with an error bar (standard deviation).

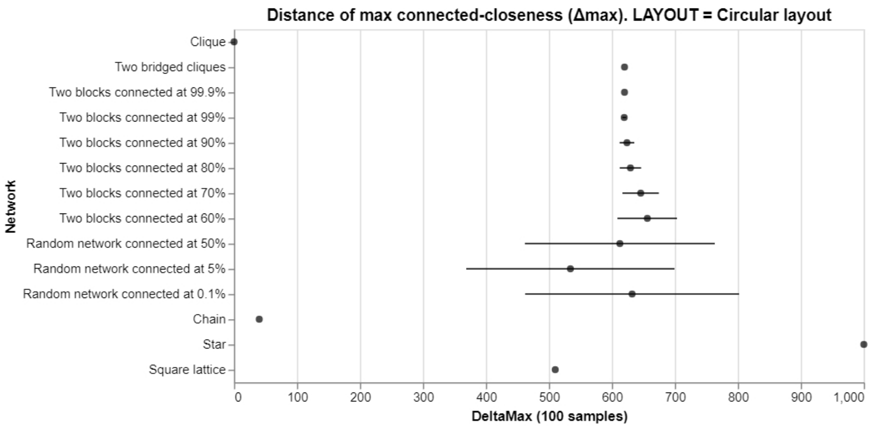


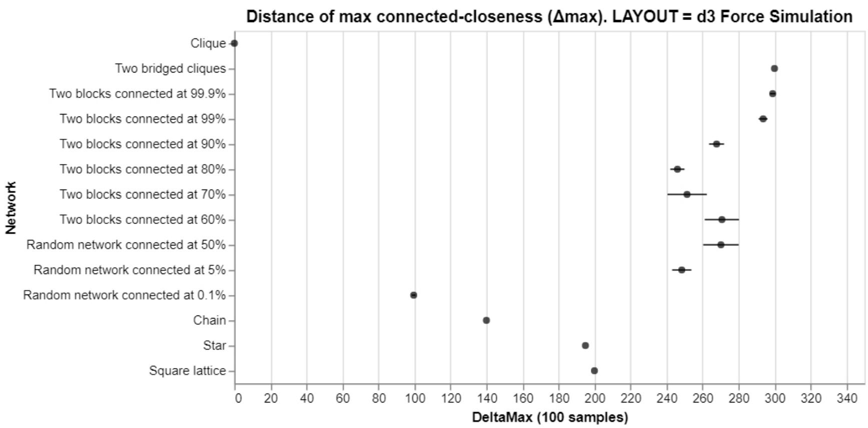



Distance of max connected-closeness (Δmax). LAYOUT = Lin Log
Network
Clique
Two bridged cliques
Two blocks connected at 99.9%
Two blocks connected at 99%
Two blocks connected at 90%
Two blocks connected at 80%
Two blocks connected at 70%
Two blocks connected at 60%
Random network connected at 50%
Random network connected at 5%
Random network connected at 0.1%
Chain
Star
Square lattice
0 50 100 150 200 250 300 350 400 450 500
DeltaMax (100 samples)


Distance of max connected-closeness (Δmax). LAYOUT = Random (disc)
Network
Clique
Two bridged cliques
Two blocks connected at 99.9%
Two blocks connected at 99%
Two blocks connected at 90%
Two blocks connected at 80%
Two blocks connected at 70%
Two blocks connected at 60%
Random network connected at 50%
Random network connected at 5%
Random network connected at 0.1%
Chain
Star
Square lattice
0 40 80 120 160 200 240 280 320 360 400
DeltaMax (100 samples)


Distance of max connected-closeness (Δmax). LAYOUT = Random (square)
Network
Clique
Two bridged cliques
Two blocks connected at 99.9%
Two blocks connected at 99%
Two blocks connected at 90%
Two blocks connected at 80%
Two blocks connected at 70%
Two blocks connected at 60%
Random network connected at 50%
Random network connected at 5%
Random network connected at 0.1%
Chain
Star
Square lattice
0 20 40 60 80 100 120 140 160 180 200 220 240 260 280 300 320 340
DeltaMax (100 samples)

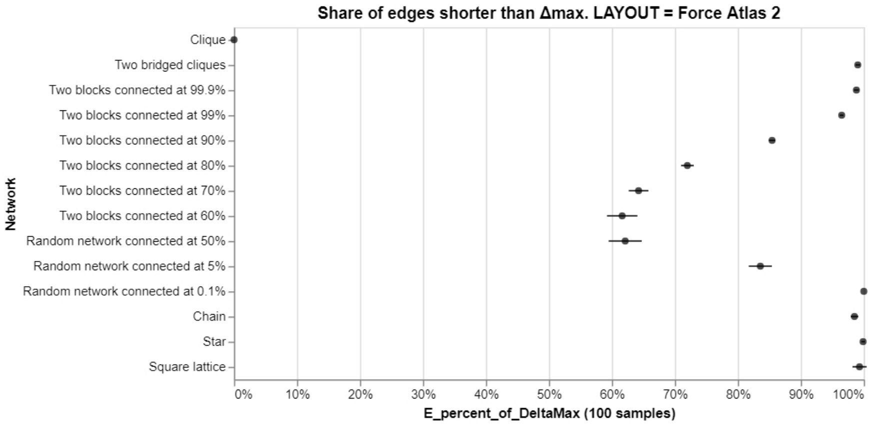

Distance of max connected-closeness (Δmax). LAYOUT = Circular layout
Network
Clique
Two bridged cliques
Two blocks connected at 99.9%
Two blocks connected at 99%
Two blocks connected at 90%
Two blocks connected at 80%
Two blocks connected at 70%
Two blocks connected at 60%
Random network connected at 50%
Random network connected at 5%
Random network connected at 0.1%
Chain
Star
Square lattice
0 100 200 300 400 500 600 700 800 900 1,000
DeltaMax (100 samples)

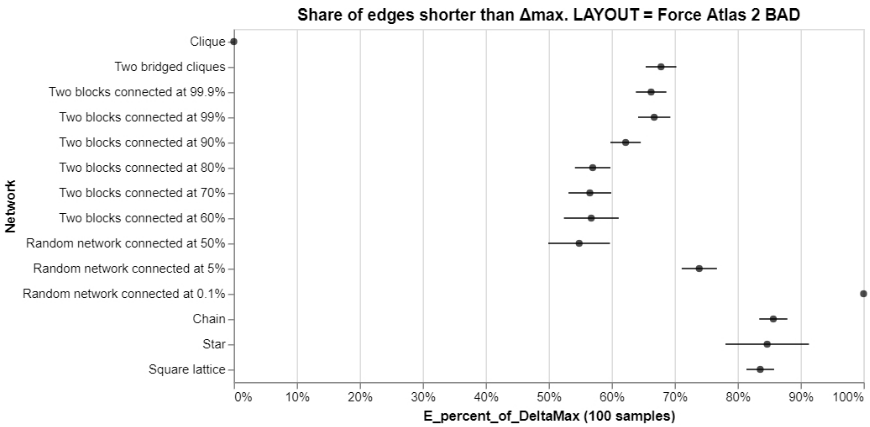

Distance of max connected-closeness (Δmax). LAYOUT = d3 Force Simulation
Network
Clique
Two bridged cliques
Two blocks connected at 99.9%
Two blocks connected at 99%
Two blocks connected at 90%
Two blocks connected at 80%
Two blocks connected at 70%
Two blocks connected at 60%
Random network connected at 50%
Random network connected at 5%
Random network connected at 0.1%
Chain
Star
Square lattice
0 20 40 60 80 100 120 140 160 180 200 220 240 260 280 300 320 340
DeltaMax (100 samples)

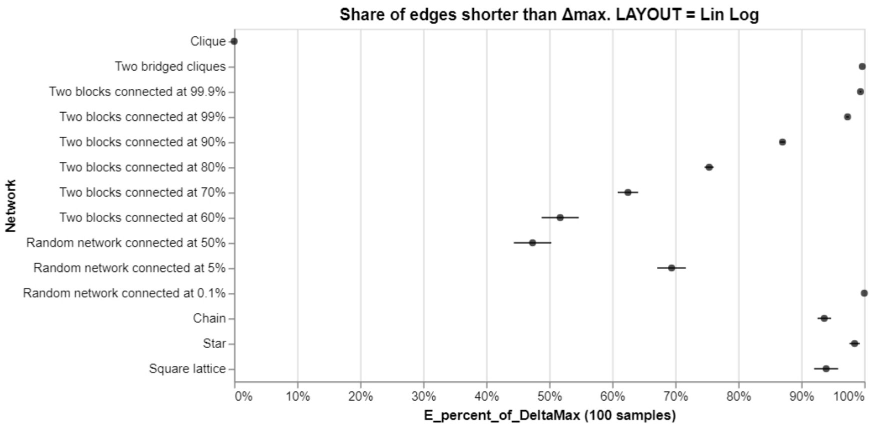
A.4 $E_{\%}(\Delta_{max})$, share of edges shorter than Δ_{max}.

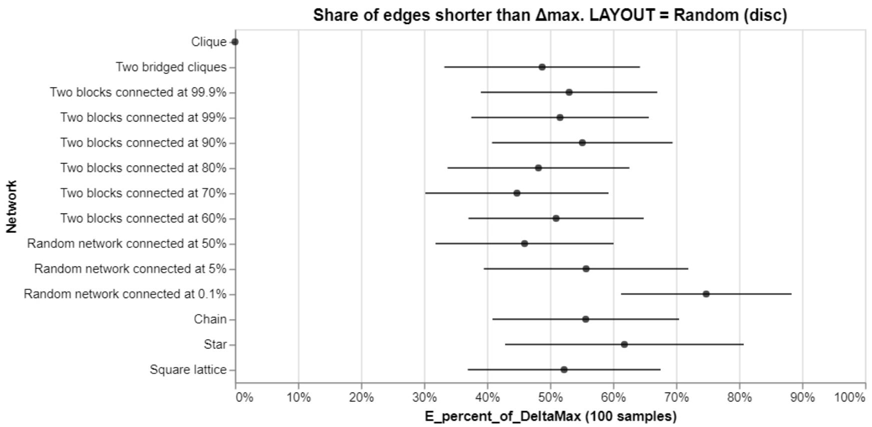
$E_{\%}(\Delta_{max})$ is a percentage of edges. For a given network, it allows comparing different layouts, and for a layout, it allows comparing different networks. It also compares to $p_{\%}(\Delta_{max})$.

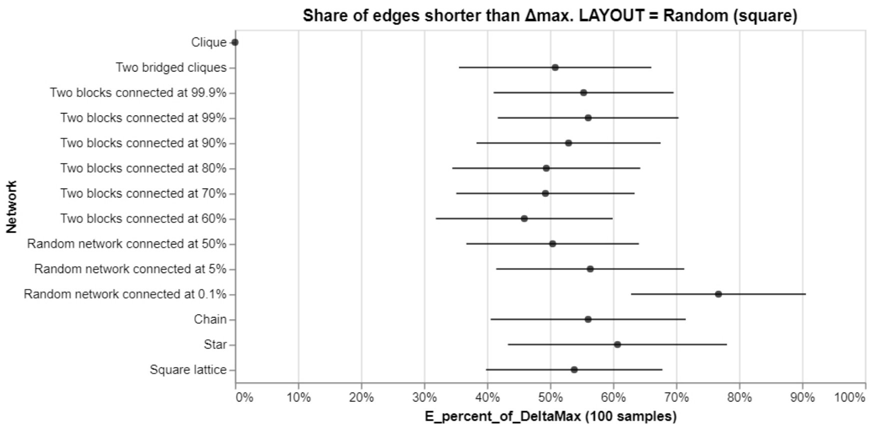
For each *(network generator, layout)* pair, the values for the 100 renditions are represented as a dot (mean) with an error bar (standard deviation).

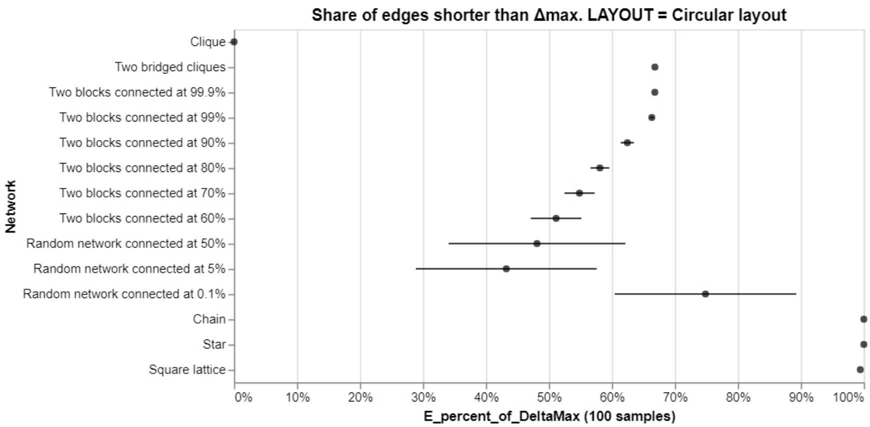


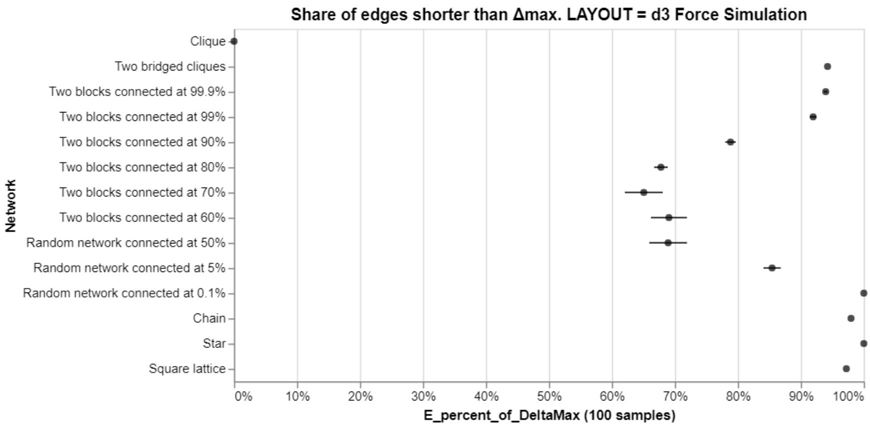



Share of edges shorter than Δmax. LAYOUT = Lin Log
Network
Clique
Two bridged cliques
Two blocks connected at 99.9%
Two blocks connected at 99%
Two blocks connected at 90%
Two blocks connected at 80%
Two blocks connected at 70%
Two blocks connected at 60%
Random network connected at 50%
Random network connected at 5%
Random network connected at 0.1%
Chain
Star
Square lattice
0%
10%
20%
30%
40%
50%
60%
70%
80%
90%
100%
E_percent_of_DeltaMax (100 samples)


Share of edges shorter than Δmax. LAYOUT = Random (disc)
Network
Clique
Two bridged cliques
Two blocks connected at 99.9%
Two blocks connected at 99%
Two blocks connected at 90%
Two blocks connected at 80%
Two blocks connected at 70%
Two blocks connected at 60%
Random network connected at 50%
Random network connected at 5%
Random network connected at 0.1%
Chain
Star
Square lattice
0%
10%
20%
30%
40%
50%
60%
70%
80%
90%
100%
E_percent_of_DeltaMax (100 samples)


Share of edges shorter than Δmax. LAYOUT = Random (square)
Network
Clique
Two bridged cliques
Two blocks connected at 99.9%
Two blocks connected at 99%
Two blocks connected at 90%
Two blocks connected at 80%
Two blocks connected at 70%
Two blocks connected at 60%
Random network connected at 50%
Random network connected at 5%
Random network connected at 0.1%
Chain
Star
Square lattice
0%
10%
20%
30%
40%
50%
60%
70%
80%
90%
100%
E_percent_of_DeltaMax (100 samples)

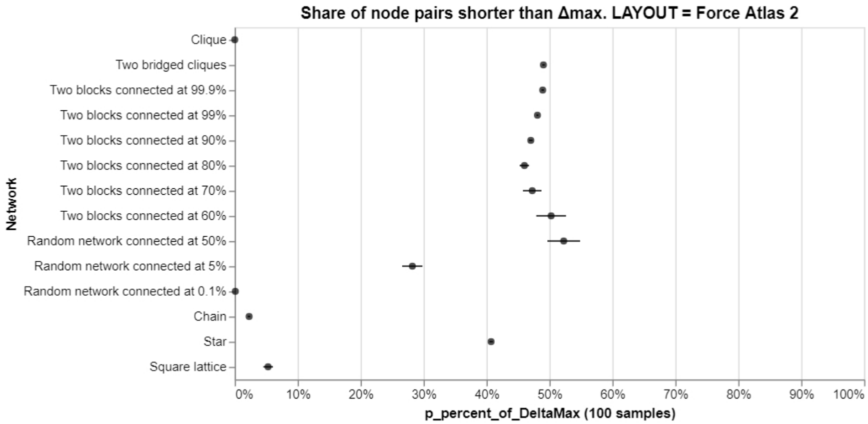

Share of edges shorter than Δmax. LAYOUT = Circular layout
Network
Clique
Two bridged cliques
Two blocks connected at 99.9%
Two blocks connected at 99%
Two blocks connected at 90%
Two blocks connected at 80%
Two blocks connected at 70%
Two blocks connected at 60%
Random network connected at 50%
Random network connected at 5%
Random network connected at 0.1%
Chain
Star
Square lattice
0% 10% 20% 30% 40% 50% 60% 70% 80% 90% 100%
E_percent_of_DeltaMax (100 samples)

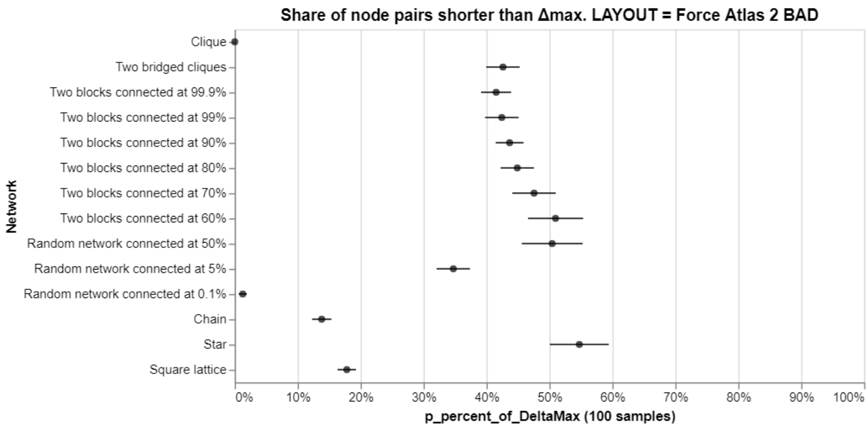

Share of edges shorter than Δmax. LAYOUT = d3 Force Simulation
Network
Clique
Two bridged cliques
Two blocks connected at 99.9%
Two blocks connected at 99%
Two blocks connected at 90%
Two blocks connected at 80%
Two blocks connected at 70%
Two blocks connected at 60%
Random network connected at 50%
Random network connected at 5%
Random network connected at 0.1%
Chain
Star
Square lattice
0% 10% 20% 30% 40% 50% 60% 70% 80% 90% 100%
E_percent_of_DeltaMax (100 samples)

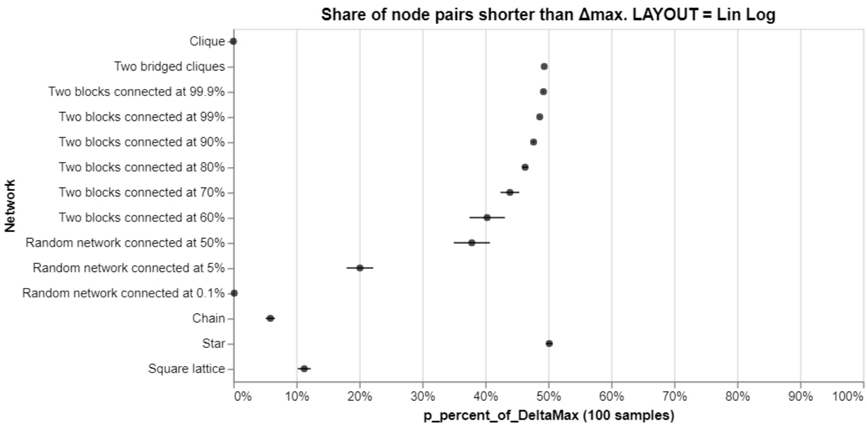
A.5 $p_{\%}(\Delta_{max})$, share of node pairs closer than Δ_{max}.

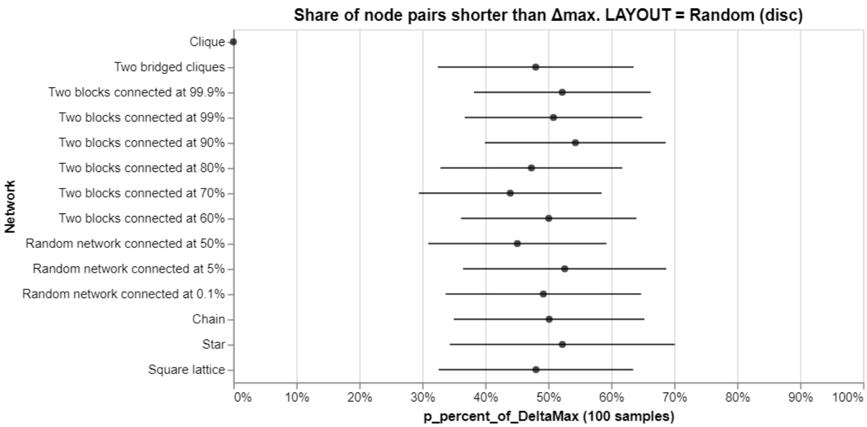
$p_{\%}(\Delta_{max})$ is a percentage of node pairs. For a given network, it allows comparing different layouts, and for a layout, it allows comparing different networks. It also compares to $E_{\%}(\Delta_{max})$.

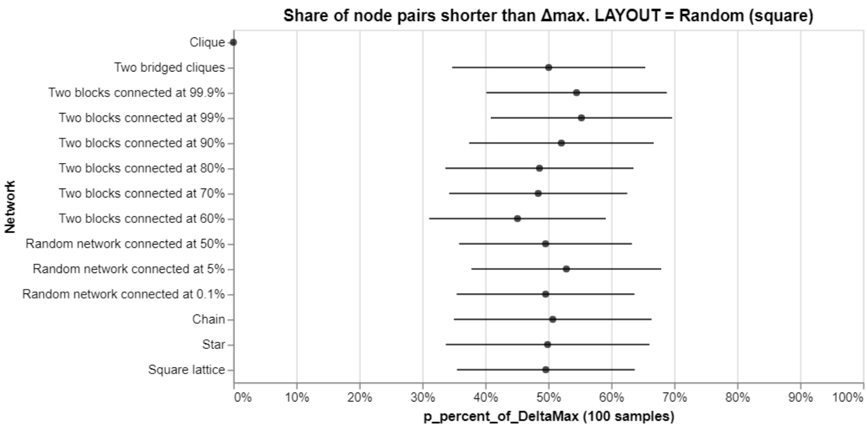
For each *(network generator, layout)* pair, the values for the 100 renditions are represented as a dot (mean) with an error bar (standard deviation).

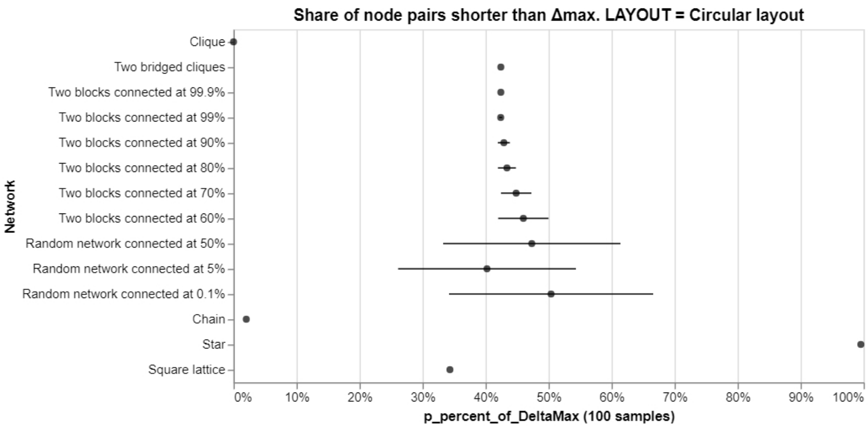


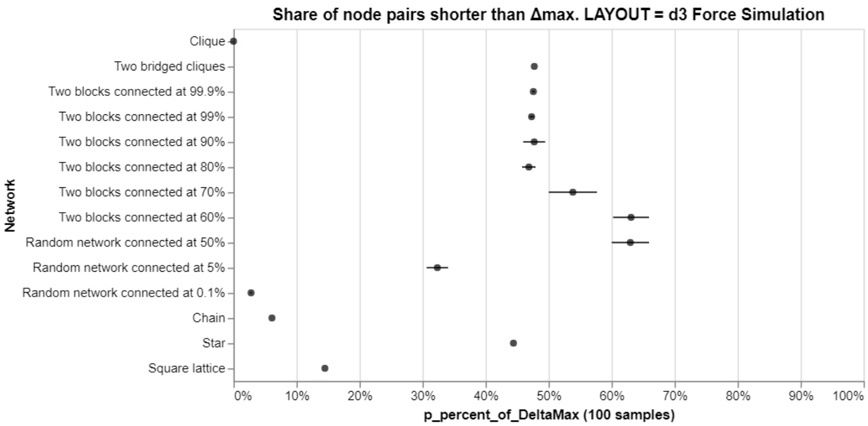



Share of node pairs shorter than Δmax. LAYOUT = Lin Log
Network
Clique
Two bridged cliques
Two blocks connected at 99.9%
Two blocks connected at 99%
Two blocks connected at 90%
Two blocks connected at 80%
Two blocks connected at 70%
Two blocks connected at 60%
Random network connected at 50%
Random network connected at 5%
Random network connected at 0.1%
Chain
Star
Square lattice
0% 10% 20% 30% 40% 50% 60% 70% 80% 90% 100%
p_percent_of_DeltaMax (100 samples)


Share of node pairs shorter than Δmax. LAYOUT = Random (disc)
Network
Clique
Two bridged cliques
Two blocks connected at 99.9%
Two blocks connected at 99%
Two blocks connected at 90%
Two blocks connected at 80%
Two blocks connected at 70%
Two blocks connected at 60%
Random network connected at 50%
Random network connected at 5%
Random network connected at 0.1%
Chain
Star
Square lattice
0% 10% 20% 30% 40% 50% 60% 70% 80% 90% 100%
p_percent_of_DeltaMax (100 samples)


Share of node pairs shorter than Δmax. LAYOUT = Random (square)
Network
Clique
Two bridged cliques
Two blocks connected at 99.9%
Two blocks connected at 99%
Two blocks connected at 90%
Two blocks connected at 80%
Two blocks connected at 70%
Two blocks connected at 60%
Random network connected at 50%
Random network connected at 5%
Random network connected at 0.1%
Chain
Star
Square lattice
0% 10% 20% 30% 40% 50% 60% 70% 80% 90% 100%
p_percent_of_DeltaMax (100 samples)

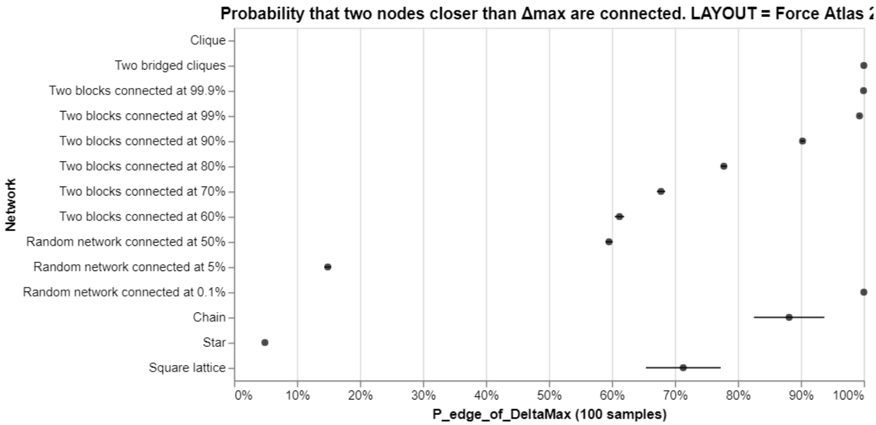

Share of node pairs shorter than Δmax. LAYOUT = Circular layout
Network
Clique
Two bridged cliques
Two blocks connected at 99.9%
Two blocks connected at 99%
Two blocks connected at 90%
Two blocks connected at 80%
Two blocks connected at 70%
Two blocks connected at 60%
Random network connected at 50%
Random network connected at 5%
Random network connected at 0.1%
Chain
Star
Square lattice
0% 10% 20% 30% 40% 50% 60% 70% 80% 90% 100%
p_percent_of_DeltaMax (100 samples)

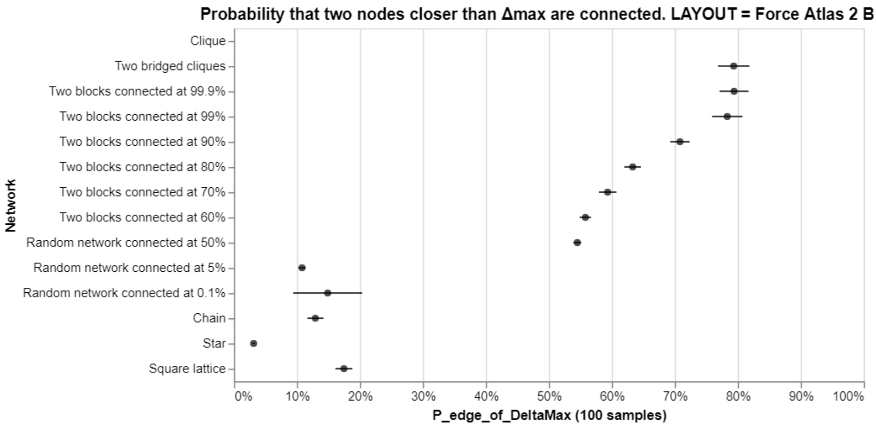

Share of node pairs shorter than Δmax. LAYOUT = d3 Force Simulation
Network
Clique
Two bridged cliques
Two blocks connected at 99.9%
Two blocks connected at 99%
Two blocks connected at 90%
Two blocks connected at 80%
Two blocks connected at 70%
Two blocks connected at 60%
Random network connected at 50%
Random network connected at 5%
Random network connected at 0.1%
Chain
Star
Square lattice
0% 10% 20% 30% 40% 50% 60% 70% 80% 90% 100%
p_percent_of_DeltaMax (100 samples)

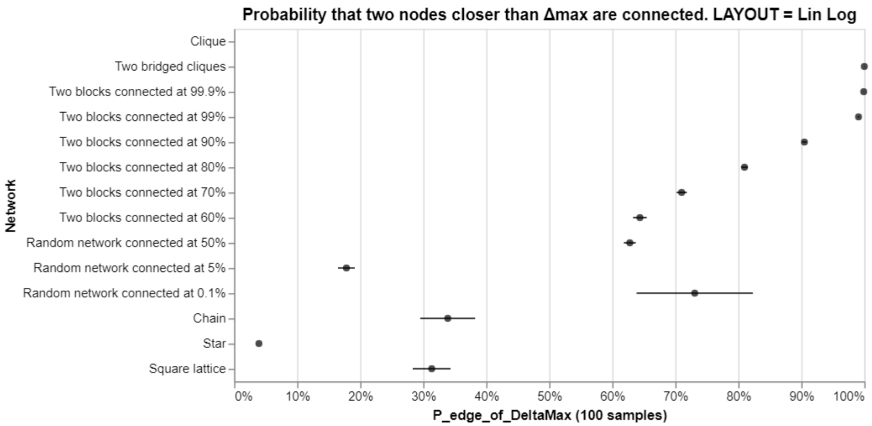
A.6 $P_{edge}(\Delta_{max})$, probability that a node pair closer than Δ_{max} is connected.

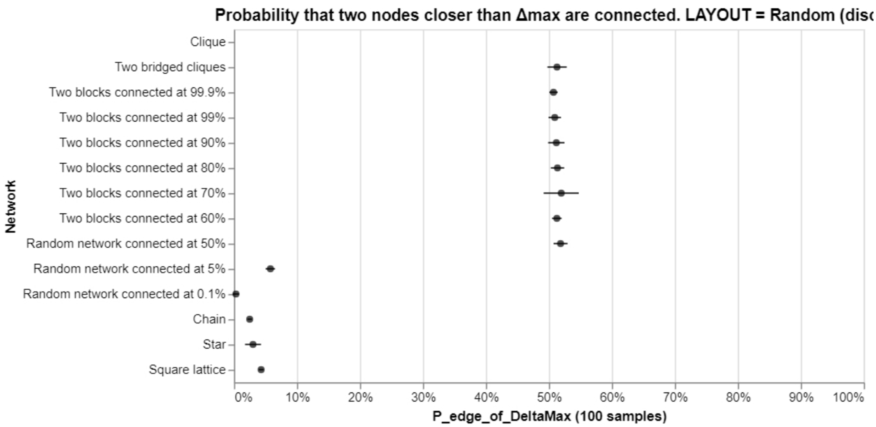
$P_{edge}(\Delta_{max})$ is a probability, expressed as a percentage. For a given network, it allows comparing different layouts, and for a layout, it allows comparing different networks.

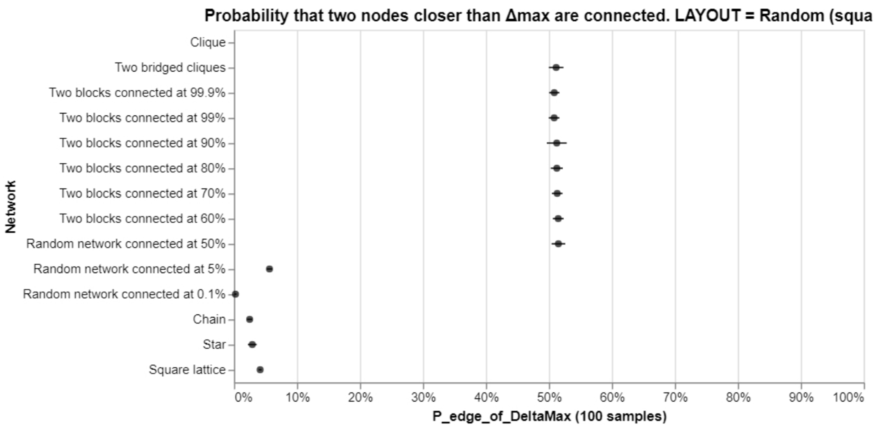
For each *(network generator, layout)* pair, the values for the 100 renditions are represented as a dot (mean) with an error bar (standard deviation).

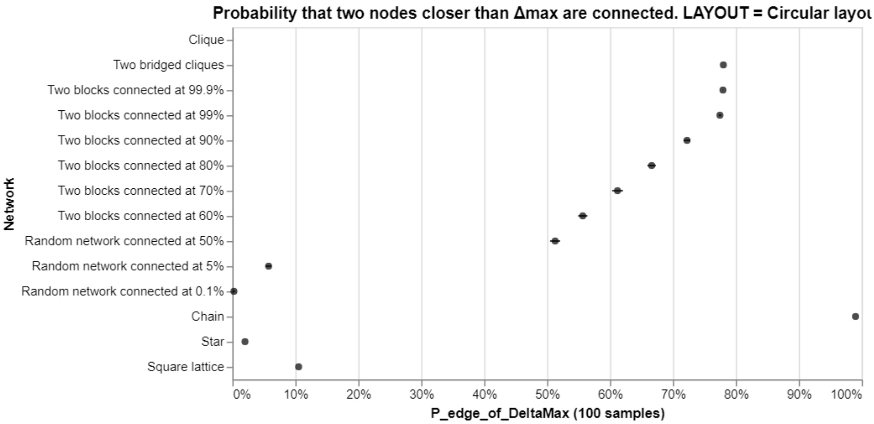


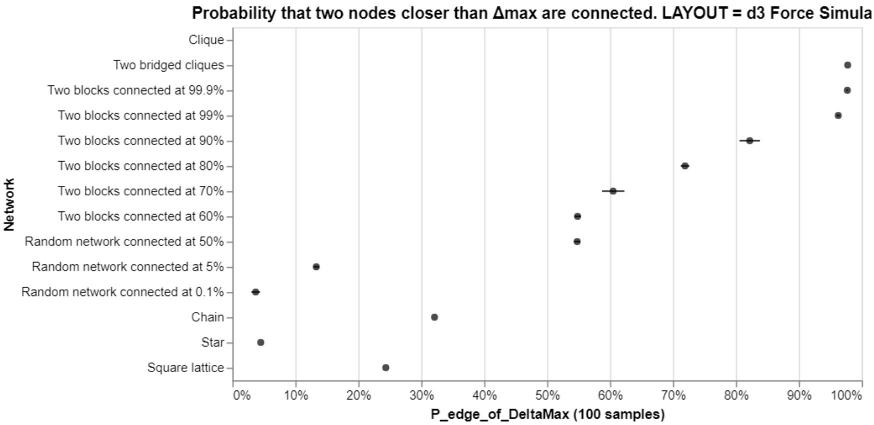



Probability that two nodes closer than Δmax are connected. LAYOUT = Lin Log
Network
Clique
Two bridged cliques
Two blocks connected at 99.9%
Two blocks connected at 99%
Two blocks connected at 90%
Two blocks connected at 80%
Two blocks connected at 70%
Two blocks connected at 60%
Random network connected at 50%
Random network connected at 5%
Random network connected at 0.1%
Chain
Star
Square lattice
0% 10% 20% 30% 40% 50% 60% 70% 80% 90% 100%
P_edge_of_DeltaMax (100 samples)


Probability that two nodes closer than Δmax are connected. LAYOUT = Random (disc
Network
Clique
Two bridged cliques
Two blocks connected at 99.9%
Two blocks connected at 99%
Two blocks connected at 90%
Two blocks connected at 80%
Two blocks connected at 70%
Two blocks connected at 60%
Random network connected at 50%
Random network connected at 5%
Random network connected at 0.1%
Chain
Star
Square lattice
0% 10% 20% 30% 40% 50% 60% 70% 80% 90% 100%
P_edge_of_DeltaMax (100 samples)


Probability that two nodes closer than Δmax are connected. LAYOUT = Random (squa
Network
Clique
Two bridged cliques
Two blocks connected at 99.9%
Two blocks connected at 99%
Two blocks connected at 90%
Two blocks connected at 80%
Two blocks connected at 70%
Two blocks connected at 60%
Random network connected at 50%
Random network connected at 5%
Random network connected at 0.1%
Chain
Star
Square lattice
0% 10% 20% 30% 40% 50% 60% 70% 80% 90% 100%
P_edge_of_DeltaMax (100 samples)


Probability that two nodes closer than Δmax are connected. LAYOUT = Circular layou
Network
Clique
Two bridged cliques
Two blocks connected at 99.9%
Two blocks connected at 99%
Two blocks connected at 90%
Two blocks connected at 80%
Two blocks connected at 70%
Two blocks connected at 60%
Random network connected at 50%
Random network connected at 5%
Random network connected at 0.1%
Chain
Star
Square lattice
0% 10% 20% 30% 40% 50% 60% 70% 80% 90% 100%
P_edge_of_DeltaMax (100 samples)


Probability that two nodes closer than Δmax are connected. LAYOUT = d3 Force Simula
Network
Clique
Two bridged cliques
Two blocks connected at 99.9%
Two blocks connected at 99%
Two blocks connected at 90%
Two blocks connected at 80%
Two blocks connected at 70%
Two blocks connected at 60%
Random network connected at 50%
Random network connected at 5%
Random network connected at 0.1%
Chain
Star
Square lattice
0% 10% 20% 30% 40% 50% 60% 70% 80% 90% 100%
P_edge_of_DeltaMax (100 samples)

APPENDIX J. SIMMELIAN DISTANCE

This document reveals the mathematics behind Simmelian distance. It is an early draft on the argument level, albeit featuring mathematical formalism. The LaTeX format is more convenient to typeset equations.

Jacomy, M. (unpublished manuscript) 'The Simmelian distance: A latent space to model force-driven network layouts'.

The Simmelian distance, a latent space to model force-driven network layouts

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Abstract

1 Definitions

A is the adjacency matrix of a weighted, undirected network with n nodes. $A_{ij} = A_{ji} \geq 0$ represents the existence and weight of the edge connecting the nodes i and j.

The Simmelian latent space is characterized by the Simmelian distance S between all pairs of nodes, represented as a matrix of same size as A. The Simmelian distance S_{ij} between two nodes i and j is characterized by a *self-referential* relation involving the Simmelian distances between i, j, and all the other nodes. A justification for this unusual characterization, and a practical way to compute the matrix S, are provided later. I favor this perspective because it is the most useful in practice. A more formal, non self-referential definition is provided in appendix.

For clarity, I approach the definition step by step.

Distances and proximities. The calculus in this paper involves different distances and proximities. Distances are the inverse of proximities, and vice-versa. As we will see, edge weights are equivalent to proximities. For consistency reasons, the distances and proximities are defined over $\mathbb{R}^+ \cup \{+\infty\}$ using the convention that $1/0 = +\infty$. This allows considering the absence of an edge as a null proximity and an infinite distance. Conversely, the Simmelian distance of a node with itself is defined as null, and its proximity with itself is infinite. As all values considered are positive, this raises no calculus issue.

I will use the $\overline{bar}$ to denote proximities: if S_{ij} is a distance, then $\overline{S}_{ij}$ is the corresponding proximity (its inverse).

Indirect Simmelian distance. Let $S_{\widehat{ikj}}$ be the indirect Simmelian distance between i and j passing by node k (figure 1).

$$S_{\widehat{ikj}} = S_{ik} + S_{kj} \tag{1}$$

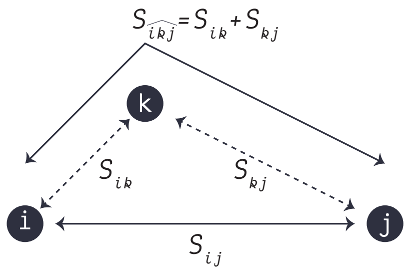

Fig. 1. Indirect Simmelian distance $S_{\widehat{ikj}}$, from i to j passing by k.

Indirect Simmelian proximity. Let $\overline{S}_{\widehat{ikj}}$ be the indirect Simmelian *proximity* betwee and j passing by node k.

$$\overline{S}_{\widehat{ikj}} = \frac{1}{S_{\widehat{ikj}}} = \frac{1}{S_{ik} + S_{kj}} \qquad ($$

Coproximity. The coproximity C_{ij} between the nodes i and j is, except for one detail, t average indirect Simmelian proximity passing by all the other nodes.

$$C_{ij} = \tfrac{1}{n} \sum_{k \neq i,j} \overline{S}_{\widehat{ikj}} = \frac{1}{n} \sum_{k \neq i,j} \frac{1}{S_{ik} + S_{kj}} \qquad ($$

Where n is the number of nodes

Note: this is not an actual average, as the sum is divided by n and not $(n-2)$. T difference gets negligible for large networks.

Interpretation: i and j have a high coproximity when many other nodes are close (in t Simmelian sense) to *both* i and j. Indeed, if a node k is far from *either* i or j, then $S_{ik} +$ is large and $\overline{S}_{\widehat{ikj}}$ is small.

Simmelian proximity. The Simmelian proximity $\overline{S}_{ij}$ between the nodes i and j is chara terized by:

$$\overline{S}_{ij} = \max\{A_{ij}, C_{ij}\} = \max\{A_{ij}, \tfrac{1}{n} \sum_{k \neq i,j} \frac{1}{S_{ik} + S_{kj}}\} \qquad ($$

Where n is the number of nodes, A the adjacency matrix

Interpretation: i and j are close either because they are strongly connected (A_{ij} high), because they are close, together, to other nodes (C_{ij} high). Possibly both.

Simmelian distance. The Simmelian distance S_{ij} between the nodes i and j is charact ized by:

$$S_{ij} = \frac{1}{\bar{S}_{ij}} = \frac{1}{\max\{A_{ij}, \frac{1}{n}\sum_{k\neq i,j}\frac{1}{S_{ik}+S_{kj}}\}} \tag{5}$$

Where n is the number of nodes, A the adjacency matrix

Same interpretation: i and j are close either because they are connected, or because they are close, together, to other nodes.

Remark: as you can see, this characterization is self-referential. It does not suffice to define S, as trivial solutions exist, such as the null matrix ($\forall ij\ S_{ij} = 0$). Intuitively, S corresponds to non-trivial solutions, where S_{ij} is non-null as often as possible. This equation (5) is the relevant one to consider in order to understand S. But formally, S is defined as the limit of a recursive relation (6).

Simmelian distance (recursive definition). The Simmelian distance S_{ij} between the nodes i and j is defined as the limit of the recursive Simmelian distance $S_{ij}(t)$:

$$\begin{cases} \forall i \quad \forall t \quad S_{ii}(t) = 0 \\ \forall i \neq j \quad S_{ij}(0) = \infty \\ \forall t \in \mathbb{N} \quad \forall i \neq j \quad S_{ij}(t+1) = \dfrac{1}{\max\{A_{ij}, \frac{1}{n}\sum_{k\neq i,j}\frac{1}{S_{ik}(t)+S_{kj}(t)}\}} \\ S_{ij} = \lim_{t\to\infty} S_{ij}(t) \end{cases} \tag{6}$$

In short, the distances between different nodes $S_{ij}(t)$ are initialized as infinite, and decrease non-strictly towards their limit S_{ij}. A formal proof of the convergence is provided in appendix (theorem 1).

Justification. The self-referential characterization (5) of S is instrumental to its ability to model the Euclidean distances produced by a force-directed network layout (or embedding). Indeed, these Euclidean distances also have a self-referential characterization. Distances depend on node coordinates, and those are computed on the basis of node distances, via attraction and repulsion forces.

The self-referential character allows a simple, plain English statement about proximity. The equation (3) can be understood as an operationalization of the statement “being close means being close, together, of others”. This is also summarizes the notion of *embeddedness* (I will develop this point shortly). The equation (5) is necessary to involve pre-existing connections (the A_{ij}) into this understanding of proximity.

This characterization is ambiguous because “being close” means two things at the same time: “being connected” and “being close, together, of others”. In other words, closeness represents both connectedness and embeddedness. This ambiguity is necessary because it is also part of force-directed layouts. Indeed, although those algorithms aim at bringing connected nodes closer, many connected nodes are nevertheless split apart (visible as long edges), and many close nodes are disconnected. Force-driven embedding distances also represent connectedness and embeddedness at the same time. Long edges represent connectedness without embeddedness, and close disconnected pairs represent embeddedness without connectedness. A model that matches the behavior of force-directed networks must replicate their inherent ambiguity. Implicitly, this argument suggests that ambiguity is part of their appeal, but I will come to that point progressively.

1.1 Properties

Let w be the maximal edge weight:

$$w = \max_{i \neq j}(A_{ij})$$

Here are a few noteworthy properties of the Simmelian distance that help building a mental model (see proofs in the appendix).

- Self-loops are ignored (by definition).
- S_{ij} and C_{ij} are positive or null (see A 9, A 11).
- $\forall i \neq j \quad \overline{S}_{ij} \leq w$ and $S_{ij} \geq \frac{1}{w}$ (see A 12)
- $\forall i \neq j \quad C_{ij} \leq \frac{w}{2}$ (see A 13)
- If i and j are in the same isolated subgraph, then S_{ij} is finite (see theorem 5).
- If i and j are in different isolated subgraphs, then $S_{ij} = \infty$ (see theorem 6).
- The Simmelian distance preserves structural equivalence (see theorem 12). $\forall k\, A_{Ik} = A_{Jk} \Longrightarrow \forall k\, S_{Ik} = S_{Jk}$

Unweighted networks. If $\forall ij\, A_{ij} \in \{0,1\}$, then:

- $\overline{S}_{ij} \leq 1$ and $S_{ij} \geq 1$ (see A 12)
- $C_{ij} \leq \frac{1}{2}$ (see A 13)
- For two *connected* nodes $i \neq j$, $S_{ij} = \overline{S}_{ij} = 1$ (see A 14).

Semimetric. The Simmelian distance is *semimetric* (see theorem 8 in appendix). In short, it behaves almost like the distance in a Euclidean space, with one difference: it does not satisfy the triangular inequality, but only a relaxed version of it.

$$\forall ij \quad \begin{cases} S_{ij} \geq 0 \\ S_{ij} = 0 \iff i = j \\ S_{ij} = S_{ji} \\ \forall k \quad S_{ij} \leq n\left(S_{ik} + S_{kj}\right) \end{cases}$$

Latent space. The Simmelian proximity matrix $\overline{S}$ is a reduction of the adjacency matrix A in the sense of a loss of information. Indeed, different adjacency matrices *can* produce identical Simmelian matrices. In particular, *any Simmelian proximity matrix is its own Simmelian proximity matrix* (see theorem 13). So A and $\overline{S}$ are different but get the same Simmelian proximity matrix $\overline{S}$. This shows that finding the proximity matrix removes some information. Information loss provides a reason why $\overline{S}$ is its own Simmelian proximity matrix: the information removed from A does not have to be removed again. This reduction is is my motivation for calling the Simmelian distances a “latent space”.

Remarkable cases.

- In a stable ($\forall i \neq j\ A_{ij} = 0$), $S_{ij} = \infty$ (see theorem 9).
- In a clique ($\forall i \neq j\ A_{ij} = 1$), $S_{ij} = 1$ (see theorem 10).
- In a clique minus one edge, the Simmelian distance between the two only disconnected nodes approaches 2 for large n (the exact value is $\frac{2n}{n-2}$). The other Simmelian distances are 1 (see theorem 11).

A Appendix: Formal definitions and proofs

A.1 Definitions

Context. The distances, edges weights, and proximities are defined in $\mathbb{R}^+ \cup \{+\infty\}$ with the convention that $\frac{1}{0} = +\infty$. This allows us defining proximity as the inverse of distance: the null distance is the infinite proximity, and the infinite distance is the null proximity.

Type of network considered. We consider a weighted undirected network with $n \in \mathbb{N}$ nodes, defined by an adjacency matrix A satisfying the following conditions:

$$\begin{cases} A_{ij} \in \mathbb{R}^+ \cup \{+\infty\} & \text{if } i = j \\ A_{ij} \in \mathbb{R}^+ & \text{if } i \neq j \\ A_{ij} = A_{ji} & \end{cases}$$

We refer to A_{ij} as the edge weight between nodes i and j, with the convention that $A_{ij} = 0$ represents the absence of edges between i and j.

This slightly unusual definition deserves an explanation. In practice, the self-loops (A_{ii}) play no role in the definition of Simmelian distance. So to a large extent, these could be ignored. However, allowing infinite values on the diagonal of the adjacency matrix allows us taking into account an important edge case. That is our motivation. Indeed, A_{ij} can sometimes represent a proximity, the inverse of a distance. Since a distance between an element and itself is null, its proximity with itself is infinite. For that reason, we formally allow infinite self-loops. But the diagonal of the matrix is not taken into account in the calculus of the Simmelian distance, so it bears no consequence in practice.

We note w the maximal edge weight, self-loops excluded. By definition, w is finite.

$$w = \max_{i \neq j}(A_{ij})$$

Definitions. The *Simmelian distance* S_{ij} between two nodes i, j is defined over $\mathbb{R}^+ \cup \{+\infty\}$, using the convention that $\frac{1}{0} = +\infty$, as the result of the following recursive process:

$$\forall t \in \mathbb{N} \quad S_{ii}(t) = 0 \tag{A 1}$$

$$\forall i \neq j \quad S_{ij}(0) = \infty \tag{A 2}$$

$$\forall t \in \mathbb{N} \quad \forall i \neq j \quad S_{ij}(t+1) = \frac{1}{\max\{A_{ij}, C_{ij}(t)\}} \tag{A 3}$$

$$\text{where} \quad C_{ij}(t) = \frac{1}{n} \sum_{k \neq i,j} \frac{1}{S_{ik}(t) + S_{kj}(t)} \tag{A 4}$$

$$S_{ij} = \lim_{t \to \infty} S_{ij}(t) \tag{A 5}$$

This definition (A 5) assumes that $S_{i,j}(t)$ converges, which is indeed the case as we will show in theorem 1. For the sake of clarity, we also define the *coproximity* C_{ij} of any two nodes i, j as:

$$C_{ij} = \frac{1}{n} \sum_{k \neq i,j} \frac{1}{S_{ik} + S_{kj}} \tag{A 6}$$

At the convergence, the equation (A 3) can then be rewritten as:

$$\forall i \neq j \quad S_{ij} = \frac{1}{\max\{A_{ij}, C_{ij}\}} \tag{A 7}$$

We also define the *Simmelian proximity* $\overline{S}_{ij} \in \mathbb{R}^+ \cup \{+\infty\}$ as the inverse of the Simmelian distance. Its relation to coproximity is then more explicit:

$$\overline{S}_{ij} = \frac{1}{S_{ij}} = \begin{cases} \max\{A_{ij}, C_{ij}\} & \text{if } i \neq j \\ \infty & \text{if } i = j \end{cases} \tag{A 8}$$

The expression (A 8) makes it visible that A_{ij}, C_{ij} and $\overline{S}_{ij}$ are commensurable: they can be seen either as proximities or as edge weights. Beyond that, (A 8) is redundant with (A 7). For the sake of consistency, the formalism of the rest of this appendix does not make use of $\overline{S}_{ij}$, using exclusively S_{ij} instead.

A.2 Interpretation

The expressions (A 6) and (A 7) allow stating the Simmelian distance in plain English. In this interpretation, “close” and “far” refer to the Simmelian distance: S_{ij} small and large, respectively. The order of magnitude of “small” is 1, as the minimum (Simmelian) distance between non-connected nodes is 2 (A 7).

The coproximity C_{ij} is high if, and only if, there are many nodes k close to i and j at the same time (A 6). **Coproximity represents the fact that two nodes are close together to other nodes**.

We read (A 7) and (A 8) as: i and j are close if, and only if, they are either connected or in coproximity. **Two nodes are close if they are connected, or if they are close, together, to other nodes** (in the sense of the Simmelian distance).

A.3 Convergence

Here we show that the Simmelian distance $S_{ij}(t)$ is positive or null (A 9), monotonically non-increasing (A 10), and thus converges (Theorem 1).

Positive or null

$$\forall ij \quad \forall t \quad S_{ij}(t) \geq 0 \tag{A 9}$$

Proof

$$\forall t \quad S_{ii}(t) \geq 0 \quad \text{from (A 1)}$$

$$\forall i \neq j \quad S_{ij}(0) \geq 0 \quad \text{from (A 2)}$$

$$\forall t > 0 \quad S_{ij}(t) \geq 0 \quad \text{from (A 3) by observing that } A_{ij} \geq 0$$

All cases covered. □

Decreasing

$$\forall ij \quad \forall t \quad S_{ij}(t+1) \leq S_{ij}(t) \tag{A 10}$$

Proof
By induction. *Base case*:

$$S_{ij}(1) = \begin{cases} 0 = S_{ij}(0) & \text{if } i = j \text{ by definition (A 1)} \\ \frac{1}{A_{ij}} \leq S_{ij}(0) = \infty & \text{if } i \neq j \text{ from (A 2) and (A 3)} \end{cases}$$

The base case $S_{ij}(1) \leq S_{ij}(0)$ is verified.

Inductive step: let us now assume that at t given, $\forall ij\ S_{ij}(t) \leq S_{ij}(t-1)$. Then:

$$\forall i,j,k \mid k \neq i,j \quad S_{ik}(t) + S_{kj}(t) \leq S_{ik}(t-1) + S_{kj}(t-1)$$

$$\Longrightarrow \forall i,j,k \mid k \neq i,j \quad \frac{1}{S_{ik}(t) + S_{kj}(t)} \geq \frac{1}{S_{ik}(t-1) + S_{kj}(t-1)} \quad \text{from (A 9)}$$

$$\Longrightarrow \forall ij \quad \sum_{k \neq i,j} \frac{1}{S_{ik}(t) + S_{kj}(t)} \geq \sum_{k \neq i,j} \frac{1}{S_{ik}(t-1) + S_{kj}(t-1)}$$

$$\Longrightarrow \forall ij \quad C_{ij}(t) \geq C_{ij}(t-1)$$

$$\Longrightarrow \forall ij \quad \max\{A_{ij}, C_{ij}(t)\} \geq \max\{A_{ij}, C_{ij}(t-1)\}$$

$$\Longrightarrow \forall ij \quad S_{ij}(t+1) \leq S_{ij}(t) \quad \text{from (A 3)}$$

The inductive step is also verified. □

Convergence

Theorem 1 (*Convergence*)
For any two nodes i and j, $S_{ij}(t)$ converges to $S_{ij} \in [0, \infty]$.

Proof
For any two nodes i and j, $S_{ij}(t)$ is positive or null (A 9) and monotonically non-increasing (A 10). □

A.4 Upper and lower bounds

Here we show that coproximity ranges in $[0, \frac{w}{2}[$ (A 11, A 13) and that Simmelian distance between distinct nodes ranges in $[\frac{1}{w}, \infty]$ (A 12), where w is the maximal edge weight $\max_{i \neq j}(A_{ij})$.

In an unweighted networks, it means that coproximity ranges in $[0, \frac{1}{2}[$ and the Simmelian distance between distinct nodes ranges in $[1, +\infty]$. Additionally, we show that in an unweighted network, connected nodes have a Simmelian distance of 1 (A 14), and disconnected nodes have a Simmelian distance that ranges in $]2, +\infty]$ (A 15).

A.4.1 Upper and lower bounds in the general case

Lower bound of coproximity

$$\forall ij \quad \forall t \quad C_{ij}(t) \geq 0 \tag{A 11}$$

Proof
From the definition (A 4), observing that Simmelian distances are positive (A 9).
□

Lower bound of distance between distinct nodes

$$\forall i \neq j \quad \forall t \quad S_{ij}(t) \geq \frac{1}{w} \tag{A 12}$$

Where w is the maximal edge weight:

$$w = \max_{i \neq j}(A_{ij})$$

Note 1: for unweighted networks $w = 1$ and thus $S_{ij}(t) \geq 1$.
Note 2: the relation is more explicit written as $\overline{S}_{ij} \leq w$.

Proof
By induction. *Base case:* the relation is true for $t = 0$ by definition (A 2).
Inductive step: let us assume that at t given, $\forall i \neq j$, $S_{ij}(t) \geq \frac{1}{\max_{i \neq j}(A_{ij})}$. Then from (A 4):

$$\forall i \neq j \quad \forall k \neq i,j \quad S_{ik}(t) + S_{kj}(t) \geq \frac{2}{\max\limits_{i \neq j}(A_{ij})}$$

$$\Longrightarrow \forall i \neq j \quad C_{ij}(t) \leq \frac{1}{n} \sum_{k \neq i,j} \frac{\max(A_{ij})}{2}$$

$$\Longrightarrow \forall i \neq j \quad C_{ij}(t) \leq \frac{\max(A_{ij})}{2}$$

$$\Longrightarrow \forall i \neq j \quad \max\{A_{ij}, C_{ij}(t)\} \leq \max_{i \neq j}(A_{ij})$$

$$\Longrightarrow \forall i \neq j \quad S_{ij}(t+1) \geq \frac{1}{\max\limits_{i \neq j}(A_{ij})} \quad \text{by definition (A 3)}$$

The base case and inductive step are verified. $\square$

Upper bound of coproximity

$$\forall ij \quad \forall t \quad C_{ij}(t) < \frac{w}{2} \tag{A 13}$$

Proof
By definition (A 4), we have $\forall i, j, t$:

$$C_{ij}(t) = \frac{1}{n} \sum_{k \neq i,j} \frac{1}{S_{ik}(t) + S_{kj}(t)}$$

Now let us remark that since $k \neq i$ and $k \neq j$, we have from (A 12):

$$\forall k \quad S_{ik}(t) \geq 1/w \quad \text{and} \quad S_{kj}(t) \geq 1/w$$

$$\Longrightarrow C_{ij}(t) \leq \frac{1}{n} \sum_{k \neq i,j} \frac{w}{2} = \frac{n-2}{2n} w$$

$\square$

A.4.2 *Upper and lower bounds in unweighted networks*

Unweighted networks are often defined by $A_{ij} \in \{0,1\}$. However, in this sub-subsection, we consider a slightly extended case where the weight of connected edges w can have another, strictly positive, finite value:

$$\begin{cases} 0 < w < +\infty \\ \forall i \neq j \quad A_{ij} \in \{0,w\} \end{cases}$$

This allows us generalizing proportionality (A 18) to the case of unweighted networks.

Distance of connected nodes in an *unweighted* network.

Let us have $w \in]0,\infty[$ and $\forall i \neq j,\ A_{ij} \in \{0,w\}$. Then:

$$\text{For two } \textit{connected} \text{ nodes } i \neq j \quad \forall t > 0 \quad S_{ij}(t) = \frac{1}{w} \tag{A 14}$$

Proof
From the definition (A 3), observing that $A_{ij} = w$ and $C_{ij}(t) < w/2$ from (A 13). □

Lower bound of distance of disconnected nodes in an *unweighted* network.

Let us have $w \in]0,\infty[$ and $\forall i \neq j,\ A_{ij} \in \{0,w\}$. Then:

$$\text{For two } \textit{disconnected} \text{ nodes } i \neq j \quad \forall t > 0 \quad S_{ij}(t) > \frac{2}{w} \tag{A 15}$$

Proof
Let us assume that i and j are distinct disconnected nodes. From (A 13) we know that:

$$\forall t \quad C_{ij}(t) < \frac{w}{2}$$

Since $A_{ij} = 0$ for disconnected nodes:

$$\max\{A_{ij}, C_{ij}(t)\} < \frac{w}{2}$$

$$\Longrightarrow S_{ij}(t+1) > 2/w \quad \text{from (A 3)}$$

The condition is true for $t > 0$, and it is true for $t = 0$ from (A 2). □

A.5 Distances within and across isolated subgraphs

Here we show that distances between two nodes are finite if they belong to the same isolated subgraph (theorem 5), and infinite if they do not (theorem 6).

As a consequence, there is no point in computing the Simmelian distances of a network with multiple isolated subgraphs. It is more efficient to compute the Simmelian distances of each isolated subgraph separately, and strictly equivalent from a mathematical standpoint.

Propagation of finite distances. In order to establish that isolated subgraphs are infinitely distant, we need to consider how, as t augments, more and more node pairs get finite distances. In a nutshell, the following happens. At $t = 0$, all distances are infinite. At $t = 1$, all connected pairs get a finite distance. Then as t augments, finite distances propagate within isolated subgraphs, leaving the distances between them infinite.

Theorem 2 (*Inequation of sums*)

$$\begin{array}{rc} \text{If} & \forall x,t \quad f(x,t+1) \leq f(x,t) \\ \text{Then} & \left[\sum_x f(x,t+1) < \sum_x f(x,t)\right] \iff \exists x \mid f(x,t+1) < f(x,t) \end{array}$$

This theorem is a necessary step for theorem 3.

Proof
Let us have, as context:

$$\forall x,t \quad f(x,t+1) \leq f(x,t)$$

From there we argue *ad absurdum*. Let us assume:

$$\begin{cases} & \sum_x f(x,t+1) < \sum_x f(x,t) \\ !\exists x \mid & f(x,t+1) < f(x,t) \end{cases}$$

$$\text{Then} \quad \forall x,t \quad f(x,t+1) = f(x,t)$$

$$\text{Thus} \quad \sum_x f(x,t+1) = \sum_x f(x,t)$$

Which contradicts our assumption. Consequently:

$$\sum_x f(x,t+1) < \sum_x f(x,t) \Longrightarrow \exists x \mid \ f(x,t+1) < f(x,t)$$

Conversely, if we have a X satisfying:

$$f(X,t+1) < f(X,t)$$

$$\text{Then since} \quad \sum_{x \neq X} f(x,t+1) \leq \sum_{x \neq X} f(x,t)$$

$$\text{We conclude that} \quad \sum_x f(x,t+1) < \sum_x f(x,t)$$

Consequently:

$$\exists x \mid \ f(x,t+1) < f(x,t) \Longrightarrow \sum_x f(x,t+1) < \sum_x f(x,t)$$

$\square$

Theorem 3 (*Propagation of finitude*)
If (and only if) two nodes i and j have each a finite distance through a third node K at t, then these nodes have a finite distance at $t+1$. Formally:

$$\left[\exists K \neq i,j \mid \begin{pmatrix} S_{iK}(t) < \infty \\ S_{Kj}(t) < \infty \end{pmatrix}\right] \quad \iff \quad S_{ij}(t+1) < \infty$$

Proof

$$\exists K \neq i,j \mid \begin{pmatrix} S_{iK}(t) < \infty \\ S_{Kj}(t) < \infty \end{pmatrix}$$

$$\iff \exists K \neq i,j \mid S_{iK}(t) + S_{Kj}(t) < \infty$$

$$\iff \exists K \neq i,j \mid \frac{1}{S_{iK}(t)+S_{Kj}(t)} > 0$$

$$\iff \sum_{k\neq i,j} \frac{1}{S_{ik}(t)+S_{kj}(t)} > 0 \quad \text{following theorem 2}$$

$$\iff C_{ij}(t) > 0 \quad \text{from (A 4)}$$

$$\iff S_{ij}(t+1) < \infty \quad \text{by definition (A 3)}$$

□

Propagation rate of finite distances

Theorem 4 (*Propagation rate of finite distances*)
Knowing the geodesic distance G_{ij} between two nodes i and j tells us at which t their distance $S_{ij}(t)$ will get finite. The geodesic distance is the shortest path length. Formally, for i, j, t given:

$$G_{ij} \leq 2^{t-1} \implies S_{ij}(t) < \infty$$

Proof
By induction. *Base case:* We need to consider t for 0 and 1.

For $t = 0$ we consider the node pairs with $G_{ij} = 0$, i.e. pairs twice the same node. Those have a Simmelian distance of 0 (A 1).

For $t = 1$ we consider the node pairs with $G_{ij} = 0$ or 1, where only the case $G_{ij} = 1$ remains to be proven. Those are connected nodes with $A_{ij} > 0$, thus $\max\{A_{ij}, C_{ij}(0)\} > 0$ and we see from (A 3) that $S_{ij}(1)$ is finite. This verifies the base case.

Inductive step: Let us assume that, for $t \geq 1$ given, we have:

$$\forall ij \quad G_{ij} \leq 2^{t-1} \implies S_{ij}(t) < \infty$$

Considering the geodesic distances of all node pairs $\{i, j\}$, we make 3 cases:

- If $G_{ij} \leq 2^{t-1}$ then *a fortiori* $G_{ij} < 2^t$ and we know that $S_{ij}(t) < \infty$.
- If $G_{ij} > 2^t$ then we do not have to consider the case in the inductive step.
- Remain only the cases where $(2^{t-1} < G_{ij} \leq 2^t)$. Let us consider those.

Since the geodesic distance is finite, at least one shortest path exists. Since $t \geq 1$ we know that $G_{ij} \geq 2$. So we can always find at least one node $K \neq i, j$ on a shortest path of length 2 or more. Let us pick K as the middle node, or one of the middle nodes in case of an odd geodesic distance.

If G_{ij} is even, then K is the middle node. Thus we have:

$$G_{iK} = G_{Kj} = \frac{G_{ij}}{2}$$

Then since $G_{ij} \leq 2^t$:

$$G_{iK} = G_{Kj} \leq \frac{2^t}{2} = 2^{t-1}$$
$$\implies \quad S_{iK} < \infty \quad \text{and} \quad S_{Kj} < \infty$$

Then by propagation (theorem 3), $S_{ij}(t+1) < \infty$.

If G_{ij} is odd, then let us pick K so that:

$$G_{iK} = \frac{G_{ij}-1}{2}$$

$$G_{Kj} = \frac{G_{ij}+1}{2}$$

Then since $G_{ij} \leq 2^t$:

$$G_{Kj} \leq \frac{2^t+1}{2} = 2^{t-1} + \frac{1}{2}$$

Since G_{Kj} is an integer:

$$G_{Kj} \leq 2^{t-1}$$

Since $G_{iK} < G_{Kj}$ we also have $G_{iK} \leq 2^{t-1}$ and we can conclude, like for the even case, by propagation (theorem 3), that $S_{ij}(t+1) < \infty$. The inductive step is thus verified. $\square$

Observation: if we know the geodesic distance between two nodes, we know we can obtain a finite $S_{ij}(t)$ at $t = 1 + \ln(G_{ij})/\ln(2)$. If we do not know it, we can replace the geodesic distance with a larger quantity, such as the diameter of the isolated subgraph, the diameter of the graph, or the order of the graph n, for instance $t = 1 + \ln(n)/\ln(2)$.

Finite distances within an isolated subgraph

Theorem 5 (*Finite distances within an isolated subgraph*)
For two nodes i and j in the *same* isolated subgraph, there is a step T where $S_{ij}(T) < \infty$.

Proof
Being in the same subgraph, their geodesic distance G_{ij} is finite. Then from theorem 4 it suffices to pick T such that $G_{ij} \leq 2^{T-1}$. $\square$

Note: as $S_{ij}(t)$ is non-increasing, $t \geq T \implies S_{ij}(t) < \infty$.

Infinite distances across isolated subgraphs

Theorem 6 (*Infinite distances across isolated subgraphs*)
For two nodes i and j in *distinct isolated subgraphs*, $\forall t,\ S_{ij}(t) = \infty$.

Proof
By induction. *Base case:* verified by definition (A 2).
Inductive step: let us assume the following for $t \geq 0$ given:

$$\forall ij \quad \left\{ G_{ij} = \infty \implies S_{ij}(t) = \infty \right\}$$

Let i and j be two nodes in different isolated subgraphs (no paths between them). No node can be in both subgraphs at the same time. Hence:

$$\forall k \quad \begin{cases} \text{either} & G_{ik} < \infty \quad G_{kj} = \infty \\ \text{or} & G_{ik} = \infty \quad G_{kj} < \infty \\ \text{or} & G_{ik} = \infty \quad G_{kj} = \infty \end{cases}$$

$$\implies \forall k \quad \begin{cases} \text{either} & S_{kj} = \infty \\ \text{or} & S_{ik} = \infty \\ \text{or} & S_{ik} = S_{kj} = \infty \end{cases}$$

$$\text{Then} \quad \forall k \quad S_{ik} + S_{kj} = \infty$$

$$\text{Then from (A 4)} \quad \forall k \quad C_{ij}(t) = 0$$

$$\text{Then from (A 3)} \quad \forall k \quad S_{ij}(t+1) = \infty$$

The inductive step is verified. $\square$

A.6 The Simmelian distance is semimetric

The Simmelian distance is semimetric: it almost qualifies as a metric, satisfying all the conditions except the triangular inequality, yet satisfying a relaxed version of it.

The Simmelian distance $S_{ij}(t)$ is a premetric by design, at any $t > 0$. However, the relaxed version of the triangular inequality is only reached at convergence, for $S_{ij} = \lim_{\infty} S_{ij}(t)$.

Premetric

Theorem 7 (*Premetric*)
The Simmelian is a premetric, i.e. it satisfies the three following conditions: positive or null, null between and only between a node and itself, symmetric. Formally:

$$\forall ij \quad \forall t \quad \begin{cases} S_{ij}(t) \geq 0 \\ S_{ij}(t) = 0 \iff i = j \\ S_{ij}(t) = S_{ji}(t) \end{cases}$$

Proof

$$\forall ij \quad \forall t \quad S_{ij}(t) \geq 0 \quad \text{from (A 9)}$$

$$\forall t \quad S_{ij}(t) = 0 \Longrightarrow i = j \quad \text{from (A 12)}$$

$$\forall t \quad S_{ij}(t) = 0 \Longleftarrow i = j \quad \text{from (A 1)}$$

Let us now prove that $S_{ij}(t) = S_{ji}(t)$, by induction.
Base case: covered at $t = 0$ by (A 1, A 2).
Inductive step: let us assume that at $t \geq 0$ given, we have $\forall ij,\ S_{ij}(t) = S_{ji}(t)$. Then:

$$C_{ij}(t) = C_{ji}(t) \quad \text{by definition (A 4)}$$

$$\text{Then since } A_{ij} = A_{ji}, \quad S_{ij}(t+1) = S_{ji}(t+1) \quad \text{from (A 3)}$$

The base case and the inductive step are verified. $\square$

Semimetric

Theorem 8 (*Semimetric*)
The Simmelian distance is a semimetric, i.e. a premetric that satisfies a relaxed version of the triangular inequality, in this case:

$$\forall ij \quad \forall k \quad S_{ij} \leq n\left(S_{ik} + S_{kj}\right)$$

Where n is the number of nodes.

Proof
Let us observe first that if $i = j$, $k = i$, or $k = j$, the proof is trivial from (A 1). Let us now assume that the three nodes concerned are different.

$$\forall t \quad \forall i \neq j \quad \forall K \neq i,j \qquad \sum_{k \neq i,j} \frac{1}{S_{ik}(t) + S_{kj}(t)} \geq \frac{1}{S_{iK}(t) + S_{Kj}(t)}$$

$$\Longrightarrow \forall t \quad \forall i \neq j \quad \forall K \neq i,j \quad C_{ij}(t) \geq \frac{1}{n} \cdot \frac{1}{S_{iK}(t) + S_{Kj}(t)} \quad \text{from (A 4)}$$

$$\Longrightarrow \forall t \quad \forall i \neq j \quad \forall K \neq i,j \quad \max\{A_{ij}, C_{ij}(t)\} \geq \frac{1}{n} \cdot \frac{1}{S_{iK}(t) + S_{Kj}(t)}$$

$$\Longrightarrow \forall t \quad \forall i \neq j \quad \forall K \neq i,j \quad S_{ij}(t+1) \leq n \cdot (S_{iK}(t) + S_{Kj}(t)) \quad \text{from (A 3)}$$

$$\Longrightarrow \forall i \neq j \quad \forall K \neq i,j \quad \lim_{t \to \infty} S_{ij}(t) \leq n \cdot \lim_{t \to \infty} [S_{iK}(t) + S_{Kj}(t)]$$

$$\Longrightarrow \forall i \neq j \quad \forall K \neq i,j \quad \lim_{t \to \infty} S_{ij}(t) \leq n \left[\lim_{t \to \infty} S_{iK}(t) + \lim_{t \to \infty} S_{Kj}(t) \right]$$

$$\Longleftrightarrow \forall i \neq j \quad \forall K \neq i,j \quad S_{ij} \leq n [S_{iK} + S_{Kj}]$$

□

A.7 Remarkable cases

Reminder: self-loops are contingent to the Simmelian distance.

Stable. A stable is a network without edges.

$$\forall i \neq j \quad A_{ij} = 0$$

Theorem 9
In a stable, all Simmelian distances are infinite.

$$\forall i \neq j \quad S_{ij} = \infty$$

Proof
From theorem 6, since each node is an isolated subgraph. □

Clique. A clique is a network where all nodes are connected.

$$\forall i \neq j \quad A_{ij} = 1$$

Theorem 10
In a clique, all Simmelian distances are 1.

$$\forall i \neq j \quad S_{ij} = 1$$

Proof
From (A 14). □

Quasi-clique. We consider a network where all node pairs are connected but one. The distance in between the disconnected nodes approaches 2 for large networks.

Theorem 11
Let us have a network of order n satisfying:

$$\forall i \neq j \quad A_{ij} = \begin{cases} 0 & \text{if } (i,j) \in \{(0,1),(1,0)\} \\ 1 & \text{else} \end{cases}$$

Then:

$$\forall i \neq j \quad S_{ij} = \begin{cases} \frac{2n}{n-2} & \text{if } (i,j) \in \{(0,1),(1,0)\} \\ 1 & \text{else} \end{cases}$$

Proof
The S_{ij} connected nodes is 1 from (A 14). For the disconnected pair, we have:

$$S_{0,1} = S_{1,0} = \frac{1}{\max\{A_{0,1}, C_{0,1}\}} \quad \text{from (A 7)}$$

$$= \frac{1}{\frac{1}{n}\sum_{k>1} \frac{1}{S_{0,k}+S_{k,1}}} = \frac{1}{\frac{1}{n} \cdot \frac{n-2}{2}}$$

$$= \frac{2n}{n-2}$$

□

A.8 Remarkable relations

Structural equivalence. Two nodes are structurally equivalent if they are connected to the same neighbors (with the same weights).

Theorem 12 (*Preservation of structural equivalence*)
Structural equivalence is preserved through S.

Let us have two structurally equivalent nodes I and J:

$$\forall k \quad A_{Ik} = A_{Jk}$$

Then we have

$$\forall k \quad S_{Ik} = S_{Jk}$$

(We remind that A and S are symmetrical: $A_{ij} = A_{ji}$ and $S_{ij} = S_{ji}$)

Proof
We prove that the relation is true at any t by induction.

Base case: verified at $t = 0$ by definition (A 2).

Inductive step: let us assume that at $t > 0$ given we have

$$\forall k \quad S_{Ik}(t) = S_{Jk}(t)$$

Then:

$$\forall k \quad C_{Ik}(t) = \frac{1}{n}\sum_{K \neq I,k} \frac{1}{S_{IK}(t)+S_{Kk}(t)} = \frac{1}{n}\sum_{K \neq I,k} \frac{1}{S_{JK}(t)+S_{Kk}(t)}$$

$$= \frac{1}{n} \sum_{K \neq J,k} \frac{1}{S_{JK}(t) + S_{Kk}(t)} + \frac{1}{n} \left[\frac{1}{S_{JI}(t) + S_{Ik}(t)} - \frac{1}{S_{JJ}(t) + S_{Jk}(t)} \right] = C_{Jk}(t)$$

$$\implies \quad \forall k \quad S_{Ik}(t+1) = S_{Jk}(t+1) \quad \text{by definition (A 3)}$$

The base case and the inductive step are verified. □

Simmelian proximity is bounded by coproximity and adjacency

$$\forall ij \quad \overline{S}_{ij} \geq C_{ij} \tag{A 16}$$

$$\forall ij \quad \overline{S}_{ij} \geq A_{ij} \tag{A 17}$$

Proof

$$\forall i \neq j \quad \overline{S}_{ij} = \max\{A_{ij}, C_{ij}\} \quad \text{by definition (A 8)}$$

$$\forall i \quad \overline{S}_{ii} = \infty \quad \text{from (A 1)}$$

□

Latent space. The Simmelian proximity matrix $\overline{S}$ is a reduction of the adjacency matrix A in the sense of a loss of information: identical adjacency matrices produce identical Simmelian matrices, yet different adjacency matrices *can* produce identical Simmelian matrices. In particular, any Simmelian proximity matrix is its own Simmelian proximity matrix. So A and $\overline{S}$ are different but get the same Simmelian proximity matrix $\overline{S}$.

Intuitively, the process of finding the proximity matrix removes some information. This explains why $\overline{S}$ is its own Simmelian proximity matrix: the information removed from A does not have to be removed again. This reduction is is our motivation to call the Simmelian distances a “latent space”.

Theorem 13 (*Reduction to Simmelian proximities*)
If $\overline{S}^A$ is the matrix of Simmelian proximities of the adjacency matrix A, then:

$$\forall A \quad \overline{S}^{\left(\overline{S}^A\right)} = \overline{S}^A$$

Proof
Let us have A, a symmetrical matrix where $A_{ij} \in [0, \infty]$. Let us have $\overline{S}^A$ its Simmelian proximity matrix, defined as such from (A 8):

$$\overline{S}^A_{ij} = \begin{cases} \max\left\{ A_{ij}, \frac{1}{n} \sum_{k \neq i,j} \frac{1}{(1/\overline{S}^A_{ik}) + (1/\overline{S}^A_{kj})} \right\} & \text{if } i \neq j \\ \infty & \text{if } i = j \end{cases}$$

Similarly, let us have $\overline{S}^{\left(\overline{S}^A\right)}$ the Simmelian proximity matrix of $\overline{S}^A$, defined as such:

$$\overline{S}^{\left(\overline{S}^A\right)}_{ij} = \begin{cases} \max\left\{ \overline{S}^A_{ij}, \frac{1}{n} \sum_{k \neq i,j} \frac{1}{(1/\overline{S}^{\left(\overline{S}^A\right)}_{ik}) + (1/\overline{S}^{\left(\overline{S}^A\right)}_{kj})} \right\} & \text{if } i \neq j \\ \infty & \text{if } i = j \end{cases}$$

Let us first observe that since the Simmelian proximity $\overline{S}$ is the inverse of the distance S (A 8), the function $\overline{S}_{ij}(t)$ is positive or null (A 9), non-decreasing (A 10), and converges to $\overline{S}_{ij} \in [0,\infty]$ (theorem 1) from an initial value of $\overline{S}_{ij}(0) = 0$ (A 2).

Let us remark what happens for $\overline{S}_{ij}^{\left(\overline{S}^A\right)}(t)$. It increases from 0 to asymptotically reach its limit $\overline{S}_{ij}^{\left(\overline{S}^A\right)}$. But we also know from (A 17) that:

$$\forall ij \quad \overline{S}_{ij}^{\left(\overline{S}^A\right)} \geq \overline{S}_{ij}^A$$

Therefore:

$$\begin{cases} \text{either} & \overline{S}_{ij}^{\left(\overline{S}^A\right)} = \overline{S}_{ij}^A \\ \\ \text{or} \quad \exists t \mid & \overline{S}_{ij}^{\left(\overline{S}^A\right)}(t) > \overline{S}_{ij}^A \end{cases}$$

Our strategy is to show that $\overline{S}_{ij}^{\left(\overline{S}^A\right)}(t)$ cannot exceed $\overline{S}_{ij}^A$. Let us unfold the proof in ordered fashion.

We prove by induction that:

$$\forall ij \quad \forall t \geq 0 \quad \overline{S}_{ij}^{\left(\overline{S}^A\right)}(t) \leq \overline{S}_{ij}^A$$

Base case: at $t = 0$, we have:

$$\forall ij \quad \overline{S}_{ij}^{\left(\overline{S}^A\right)}(0) = 0 \quad \text{from (A 2)}$$

$$\forall ij \quad \overline{S}_{ij}^A \geq 0 \quad \text{from (A 9)}$$

$$\Longrightarrow \quad \forall ij \quad \overline{S}_{ij}^{\left(\overline{S}^A\right)}(0) \leq \overline{S}_{ij}^A$$

The base case is verified.

Inductive step: let us assume that at $t \geq 0$ given, we have

$$\forall ij \quad \overline{S}_{ij}^{\left(\overline{S}^A\right)}(t) \leq \overline{S}_{ij}^A$$

Then:

$$\forall ij \quad \sum_{k \neq i,j} \frac{1}{(1/\overline{S}_{ik}^{\left(\overline{S}^A\right)}(t)) + (1/\overline{S}_{kj}^{\left(\overline{S}^A\right)}(t))} \leq \sum_{k \neq i,j} \frac{1}{(1/\overline{S}_{ik}^A) + (1/\overline{S}_{kj}^A)}$$

$$\Longrightarrow \quad \forall ij \quad \max\left\{\overline{S}_{ij}^A, \tfrac{1}{n} \sum_{k \neq i,j} \frac{1}{(1/\overline{S}_{ik}^{\left(\overline{S}^A\right)(t)}) + (1/\overline{S}_{kj}^{\left(\overline{S}^A\right)(t)})}\right\}$$

$$\leq \quad \max\left\{\overline{S}_{ij}^A, \tfrac{1}{n} \sum_{k \neq i,j} \frac{1}{(1/\overline{S}_{ik}^A) + (1/\overline{S}_{kj}^A)}\right\}$$

$$\Longleftrightarrow \quad \forall ij \quad \overline{S}_{ij}^{\left(\overline{S}^A\right)}(t+1) \leq \max\left\{\overline{S}_{ij}^A, \frac{1}{n} \sum_{k \neq i,j} \frac{1}{(1/\overline{S}_{ik}^A) + (1/\overline{S}_{kj}^A)}\right\}$$

By definition, we know that:

$$\forall ij \quad \frac{1}{n}\sum_{k\neq i,j}\frac{1}{(1/\overline{S}^A_{ik})+(1/\overline{S}^A_{kj})} \leq \overline{S}^A_{ij}$$

Hence:

$$\forall ij \quad \overline{S}^{\left(\overline{S}^A\right)}_{ij}(t+1) \leq \overline{S}^A_{ij}$$

Which verifies the inductive step.

By induction, this proves that:

$$\forall ij \quad \forall t \geq 0 \quad \overline{S}^{\left(\overline{S}^A\right)}_{ij}(t) \leq \overline{S}^A_{ij}$$

Therefore:

$$\forall ij \quad \overline{S}^{\left(\overline{S}^A\right)}_{ij} = \lim_{t\to\infty}\left[\overline{S}^{\left(\overline{S}^A\right)}_{ij}(t)\right] \leq \overline{S}^A_{ij}$$

But since from (A 17) we also know that:

$$\forall ij \quad \overline{S}^{\left(\overline{S}^A\right)}_{ij} \geq \overline{S}^A_{ij}$$

We can conclude that:

$$\forall ij \quad \overline{S}^{\left(\overline{S}^A\right)}_{ij} = \overline{S}^A_{ij}$$

□

Proportionality. The Simmelian proximity matrix $\overline{S}^A$ varies proportionally to the adjacency matrix A.

$$\forall \alpha \geq 0 \qquad B = \alpha A \implies \overline{S}^B = \alpha \overline{S}^A \tag{A 18}$$

Proof

Let us have:

$$\forall ij \quad B_{ij} = \alpha A_{ij}$$

Let us first remark that:

$$\forall i \quad \overline{S}^B_{ii} = \overline{S}^A_{ii} = 0 \quad \text{from (A 1)}$$

For non-identical nodes, we argue by induction.

Base case: at $t = 0$ we have:

$$\forall i \neq j \quad \overline{S}^B_{ij}(0) = \max\left\{B_{ij}, \frac{1}{n}\sum_{k\neq i,j}\frac{1}{(1/\overline{S}^B_{ik}(0))+(1/\overline{S}^B_{kj}(0))}\right\}$$

$$= \max\left\{B_{ij}, \frac{1}{n}\sum_{k\neq i,j}\frac{1}{(1/0)+(1/0)}\right\}$$

$$= \max\left\{B_{ij}, 0\right\} = \max\left\{\alpha A_{ij}, 0\right\} = \alpha \max\left\{A_{ij}, 0\right\}$$

$$= \alpha \overline{S}^A_{ij}(0)$$

The base case is verified.

Inductive step: let us assume that at $t \geq 0$ given we have:

$$\forall i \neq j \quad \overline{S}^B_{ij}(t) = \alpha \overline{S}^A_{ij}(t)$$

$$\implies \quad \forall i \neq j \quad \sum_{k \neq i,j} \frac{1}{(1/\overline{S}^B_{ik}(t)) + (1/\overline{S}^B_{kj})} = \alpha \sum_{k \neq i,j} \frac{1}{(1/\overline{S}^A_{ik}(t)) + (1/\overline{S}^A_{kj})}$$

$$\begin{aligned} \implies \quad \forall i \neq j \quad & \max\left\{ B_{ij}, \tfrac{1}{n} \sum_{k \neq i,j} \frac{1}{(1/\overline{S}^B_{ik}(t)) + (1/\overline{S}^B_{kj})} \right\} \\ = \quad & \max\left\{ B_{ij}, \tfrac{\alpha}{n} \sum_{k \neq i,j} \frac{1}{(1/\overline{S}^A_{ik}(t)) + (1/\overline{S}^A_{kj})} \right\} \end{aligned}$$

$$\implies \quad \forall i \neq j \quad \overline{S}^B_{ij}(t+1) = \max\left\{ \alpha A_{ij}, \frac{\alpha}{n} \sum_{k \neq i,j} \frac{1}{(1/\overline{S}^A_{ik}(t)) + (1/\overline{S}^A_{kj})} \right\}$$

$$\implies \quad \forall i \neq j \quad \overline{S}^B_{ij}(t+1) = \alpha \max\left\{ A_{ij}, \frac{1}{n} \sum_{k \neq i,j} \frac{1}{(1/\overline{S}^A_{ik}(t)) + (1/\overline{S}^A_{kj})} \right\} = \alpha \overline{S}^A_{ij}(t+1)$$

The inductive step is verified, therefore we proved by induction that:

$$\forall t \quad \forall i \neq j \quad \overline{S}^B_{ij}(t) = \alpha \overline{S}^A_{ij}(t)$$

$$\implies \quad \forall i \neq j \quad \lim_{t \to \infty} \overline{S}^B_{ij}(t) = \alpha \lim_{t \to \infty} \overline{S}^A_{ij}(t)$$

$$\iff \quad \forall i \neq j \quad \overline{S}^B_{ij} = \alpha \overline{S}^A_{ij}$$

□