Fundamentals of Visualizing Communication Networks

Jürgen Pfeffer
School of Computer Science, Carnegie Mellon University, Pittsburgh, USA

Abstract: The human brain is built to process complex visual impressions within milliseconds. In comparison with sequentially coded spoken language and written texts, we are capable of consuming graphical information at a high bandwidth in a parallel fashion, producing a picture worth more than a thousand words. Effective information visualization can be a powerful tool to capture people's attention and quickly communicate large amounts of data and complex information. This is particularly important in the context of communication data, which often describes entities (people, organizations) and their connections through communication. Visual analytics approaches can optimize the user-computer interaction to gain insights into communication networks and learn about their structures. Network visualization is a perfect instrument to better communicate the results of analysis. The precondition for effective information visualization and successful visual reasoning is the capability to draw "good" pictures. Even though communication networks are often large, including thousands or even millions of people, underlying visualization principles are identical to those used for visualizing smaller networks. In this article, you will learn about these principles, giving you the ability to assess the quality of network visualizations and to draw better network pictures by yourself.
Key words: communication networks, information visualization, visual analytics, human perception

I. Introduction

Networks consist of entities (nodes) and their relations (links). People form phone networks when they call each other. Students work together on projects and establish collaboration networks. Twitter users *re-tweet* other users' tweets. Facebook users create *friendship* networks and *like* books, music, and other users' statements. For all these purposes, and many more, networks of real-world people or online users are formed through communication. In order to study communication networks, two main factors have been essential, the development of measurement [15] and visualization [4]. The focus of this article is on the latter.

In recent years, visualizations of communication networks have become omnipresent. Users of social media platforms can visualize their personal networks with built-in apps and traditional media use network pictures to show the complex relations of politicians, companies, or even terrorists. With network drawings, scientists are able to visualize analytical research results in a communicative way. Presenting outcomes is a common application of network visualizations, however they are not only for use at the end of a research project; visually exploring network data can yield additional insights into network structure. Although drawing networks is more complex than clicking the "Draw" button of a social network analysis tool, a basic knowledge of certain techniques can increase the quality of your visualizations dramatically, e.g., positioning the nodes, using visual elements to map information, communicating with colors, and accounting for human perception. These techniques, explored in the following sections of this article, make visualizing networks into a craft rather than an art.

There are different approaches to visualizing communication network data [6], but most of those found in research literature and non-scientific media are "point-and-line" pictures similar to Moreno's 1934 visualization of the relations within a school class (Figure 1). Jacob Levy Moreno, born in 1889 in Bucharest, is the founder of sociometry. Seen as a precursor to social network analysis, it utilizes a graphical representation of data called a "sociogram." Moreno collected these data by asking every child in a school class which two classmates should sit alongside him or her. In this figure, the nodes (the children) are visualized as triangles (boys) and circles (girls). The lines in the diagram represent the relations (edges) between the children. The analyzed relationship is directed, and therefore, the lines are drawn as arcs to represent that direction. If A chose B, then a line goes from node A to node B. You will also find lines with markings in the middle; these represent reciprocal selections.

Moreno [10] drew his networks by hand, but in the following decades, scientists standardized drawing procedures and began using computers to create network visualizations. The image in Figure 1 is almost 80 years old and rather simple, yet representative of the majority of present-day network pictures because they all draw from a very limited set of standard elements (e.g., positioning of nodes, use of different shapes to visualize different node attributes).

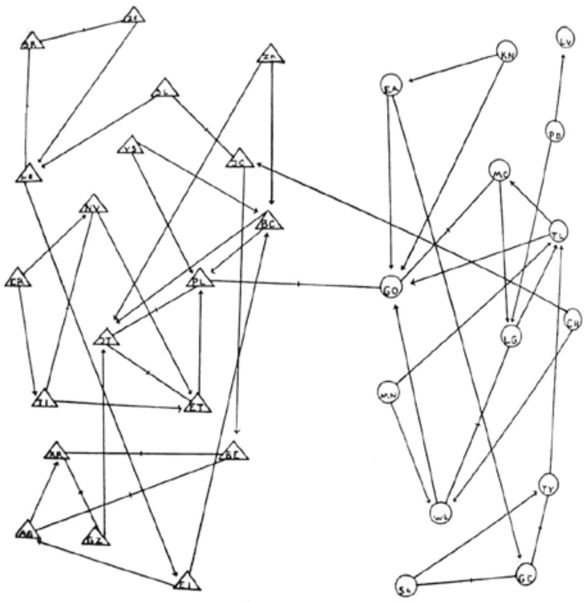


Fig.1 *1934 Sociogram by Moreno [10]*

II. VISUAL ELEMENTS

Communication network data are multivariate. Besides relational information, additional data about the nodes of a network are almost always available (e.g., gender and age of people) or can be calculated (centrality metrics show the importance of nodes). Mapping these data to a network picture can be an "effective translation of information to a system of visual elements", as Jacques Bertin, a French cartographer (1918-2010), stated in his *Semiology of Graphics* [2] (first published in French in 1967). Bertin introduced the concept of *visual elements* and defined the *retinal variables*: position, size, color value, color saturation, orientation, shape, and texture. These variables are pre-attentive, meaning that our brains process information about them in large quantity without our intention. The challenge in the context of visualizing communication networks is to use these elements to transmit information.

Mackinlay [9] reviewed Bertin's design elements for the visualization of relational information regarding perception. In Table 1, you can find the elements ordered by their suitability to communicate quantitative, ordinal, and nominal attributes. *Size*, for example, is a good fit to communicate quantitative information (e.g., centrality scores) and a very bad one for nominal data (e.g., gender) whereas *position* is the most important design element for all data categories. Nodes are specially positioned (e.g., on top of the picture in a hierarchical network or in the center in a circular layout) and are perceived as important regardless of which type of data is visualized. In many network analytical projects, a central question is the structure of the network. Consequently, position is often used to answer this question by optimizing the nodes, using a layout algorithm whereby "central" nodes are mapped in the center of the picture and "peripheral" nodes are drawn closer to the borders. Other variables include: *color saturation* (light-dark intensity), *color hue* (shade, as in red, green, blue, etc.), *size* (referring to the area of the nodes in the visualization), *shape* (differentiates nodes), and finally, *texture* (used sparingly to describe the pattern of node surfaces).

Table I *Suitability of visual elements to map quantitative, ordinal and nominal attributes, based on Mackinlay [9]*

Suitability	Quantitative	Ordinal	Nominal
very good	Position	Position	Position
↑	Size	Saturation	Hue
	Saturation	Hue	Texture
	Hue	Texture	Saturation
↓	Texture	Size	Shape
very bad	Shape	Shape	Size

III. DRAWING COMMUNICATION NETWORKS

As mentioned, the first and most important task in drawing networks is the question of where to place the nodes. The requirement for a "good" layout is that the positions of the nodes reveal the structure of the network in a visually intuitive manner. When looking at Moreno's picture (Figure 1), you can see two almost separated groups–the girls (circles) at right and the boys (triangles) at left. The positions of the nodes tell us the underlying story that boys and girls are almost disconnected in this network. Upon visual exploration of this structural pattern, a salient narrative is perceived, which lends itself to interpreting the data. Moreno arranged the nodes in his sociograms manually. In contrast, modern network analysis uses rule-based layout algorithms to reveal the inner structure of a network. These can be intuitive, but may also be quite sophisticated.

Layout algorithms can be divided into two groups. "Distance scaling" algorithms portray nodes that reject each other as disconnected and nodes that share an attraction as connected. These attracting and rejecting forces are modeled in similar fashion to physics models in which edges are interpreted as springs that push and pull towards their spring constant. Hence, these algorithms are called "spring-embedded". The best-known algorithms of this sort–advantageous for their availability and traceability–are based on the work of Fruchterman and Reingold [5] and Kamada and Kawai [7], and are implemented in almost every network analytical tool. A local optimization approach is their main disadvantage; no two layouts of the same network look the same and the outcome of a layout calculation depends on the starting position of the nodes. The second approach is called "classical scaling" and is based on multidimensional scaling [13]. These algorithms produce two- or three-dimensional representations of high-dimensional data. Classical scaling algorithms find a global maximum for every network. Independent of the starting positions of the nodes, different calculations within the same network have the exact same outcome. A disadvantage of MDS approaches is the mathematical rigor required of the algorithm user in the event that no analytical tools are available. Historically, an essential problem of all layout algorithms has been managing calculation time as the network gets larger. In fact, until recent improvements were shown to potentially resolve this problem [3], a network of more than a few thousand nodes was too expensive time-wise to be practicable.

Despite other differences across algorithms, the goals of positioning the nodes remain very similar; to "show the structure" of the network data is always most important. If the network has a globally organized structure, the layout should uncover it (e.g., if there are two almost separated groups like in Figure 1, then the picture should show this structural characteristic). One way these patterns are revealed is by "optimizing path distances." The path distances (how many steps you need from one node to another) should be represented as the distances of the nodes in the picture such that two adjacent nodes are drawn near each other while two very distant nodes are drawn farther apart. Other criteria are aesthetic in nature, but turn out to be important for readability of the network visualization. Line crossings cause confusion because they make it more difficult to trace connections. Very acute angles produce overlapping lines while obtuse angles increase the quality of the picture. Finally, all lines should have approximately the same length unless different lengths represent different line weights.

It is entirely impossible to meet these criteria when dealing with complex networks. Furthermore, any visualization (with the exception of very trivial networks) is distorted because of the projection of multidimensional relational data onto a two- or three-dimensional visualization. A layout algorithm for networks can be understood as a process that minimizes the distortion normally resultant from this projection. Although it is impossible to perfectly represent network structure with visualizations (or any known modeling technique for that matter), a good visualization can reveal important insights into one's data. This is particularly the case when additional information is mapped to the network picture.

IV. VISUALIZING INFORMATION

In Table 1, the visual elements and their suitability to map quantitative, ordinal, and nominal attributes are listed. We have just discussed *position*. To illustrate the way the other elements can be applied for an "efficient communication of information" [14], a real-world data set is selected. In the year 2004, Josh On[1] collected information on the boards of the fortune 500 companies in the United States. The network data is what network analysts call, a *two-mode* network, as two different types of nodes are collected, managers and companies. The links in the network connect managers with companies in the event that a manager serves on the board of a company. As managers serve on more than one board and companies have more than one manager on their boards, a connected network is formed. Two-mode networks of people and "affiliations" can be seen as indirect *communication* networks as we have no information about the actual communication of these managers. Instead, we infer from shared activities that communication is most likely. For the purposes of this example, we focus only on the top 10 companies based on revenue and companies that are connected to managers of those top 10 companies. There are six variables we want to map in our picture: the structure of the network consisting of

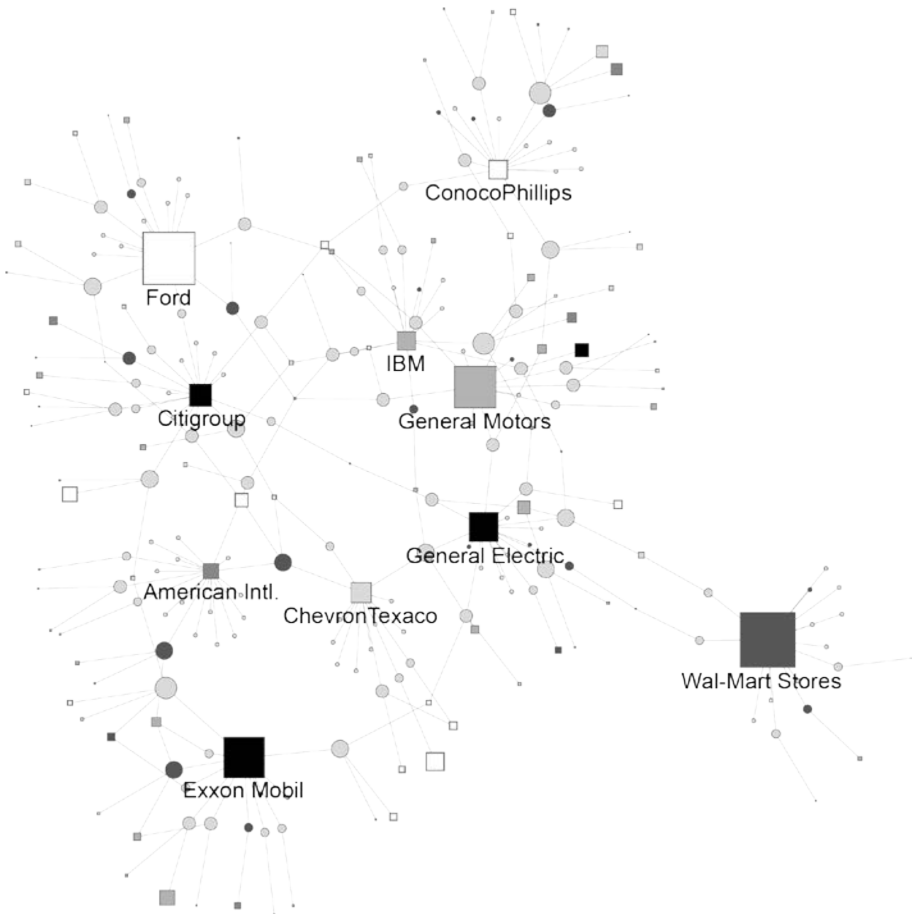


Fig.2 *Multivariate network visualization of managers and US companies.*

companies and managers, types of nodes (companies and managers), company revenue, manager gender, company profit, and the number of boards to which a manager is connected.

Figure 2 is the result of the multivariate mapping procedure. The *positions* of the nodes are automatically calculated with a layout algorithm and the network structure is used to visualize the connectivity of the selected companies. The *shape* element is used to mark the two different groups of nodes: managers with circles and companies with squares. The *sizes* of the nodes have two different meanings. For companies, it represents the revenue and for managers, it is the number of boards to which they are connected within the fortune 500 network. The *color saturation* represents manager gender (light gray = man, dark gray = women) and the profit of the companies (the darker the node, the higher the profit; negative profit is colored white). We will skip the interpretation of the picture with regards to content at this point, as the goal of this work was not to analyze the US economy, but rather to illustrate the usage of visual elements to produce multivariate visualizations. By mapping the structure of the network (nodes and links), attribute data (gender, revenue, profit), and calculated data (number of connections) to the network visualization, a data-rich–and also pretty–picture was created.

V. COMMUNICATING WITH COLORS

Looking at Figure 2, you can see that one important visual element is missing: *color hue*. There are two reasons for avoiding the use of different colors in this figure. First, in the context of scientific publications, it is often not possible, as many journals are printed in black and white. This figure is an example of how it is possible to successfully visualize a set of variables without the need for colors. Second, color hue is the visual element that is most often used incorrectly from an information visualization standpoint; they are either used to redundancy (e.g., blue boxes and red circles) or are confusing due to the colors providing irreproducible information. When used wisely, color juxtaposition can communicate data variables (primarily nominal attributes) or highlight certain areas of the visualization to attract the viewer's attention.

The main challenge of using colors to communicate information is deciding whether they are used to show differences or similarities. This has a lot to do with people's perception of colors. Figure 3 depicts a visualization of two networks consisting of three nodes each, which differ by the colors used in them. In the left network, the yellow and orange nodes are perceptually closer to each other than the blue node, creating the impression that the former two represent similar entities. In the network on the right, the three colors are intended to be perceived as uniformly distinct from each other and, consequently, their applications would be equally different. For instance, when business areas of peoples employers are visualized, the left color selection can represent banks, insurance companies, and heavy industry because the former two areas are perceived to be closer to each other that the latter. On the other hand, if the color attribute represents the three business sectors (primary, secondary, and tertiary) then the right color combination would be more appropriate. Another example for grouping with colors can be seen in Figure 6(b).

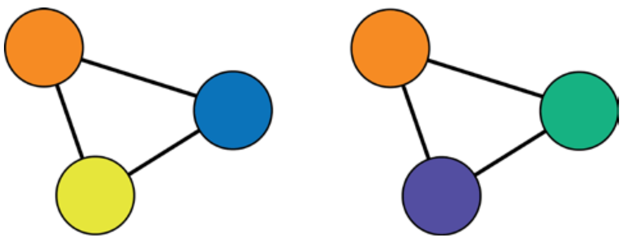


Fig.3 *Colors to show similarities and differences.*

Early on, scientists, philosophers, and artists were interested in the perception of colors and how to use this knowledge to create even more compelling pictures. Goethe's color wheel is a well-known but not entirely correct attempt to order all colors on a circle (without beginning or end). Although Goethe was very confident about his knowledge[1] when he published his "Theory of Colors" in 1810, he failed to correctly identify the colors on his wheel so that the perceptual differences between neighboring colors were equal. About a hundred years later, Albert Henry Munsell [11] offered a superior system. Although many other color schemes have been invented in the hundred years since then, Munsell's colors–described by their hue (color tint), chroma (saturation), and value (brightness)–are still widely used. Figure 4 shows a part of Munsell's color system. Each sector contains different color hues The figure visualizes the principle hues (red, yellow, green, blue, and purple) and the intermediate hues only; there are 100 sub-hues in total. Different chroma values are represented as different distances from the white or gray center of the wheel to the fully colored periphery. Different values can be imagined with darker and brighter layers, forming a third dimension. For Figure 4 the value is 6.

The most noteworthy advantage of perceptually based color systems is that one can literally calculate perfect combinations and matching gradients. Therefore, Munsell's system can be used to select a set of colors for network visualizations. For example, should we need to represent four different groups of nodes, any square that can be drawn on this picture will result in the inevitable selection of four perceptually dissimilar colors. An isosceles triangle gives us the above mentioned combination of two plus one colors. When saturations for two or more colors are needed, say, to visualize quantitative information in different categories, then just the chroma needs to be changed to guarantee perceptually continuous color gradients within a given color as well as between colors.

The main disadvantage of using perceptual color systems is that they are not standard for monitors, TVs, and printers. Of course, there are equations and algorithms to transform standard monitor (RGB) and printer (CMYK) colors to Munsell colors and vice versa. However, that process is beyond the scope of this article. For those interested in using these color systems, there are many tools online to assist you.

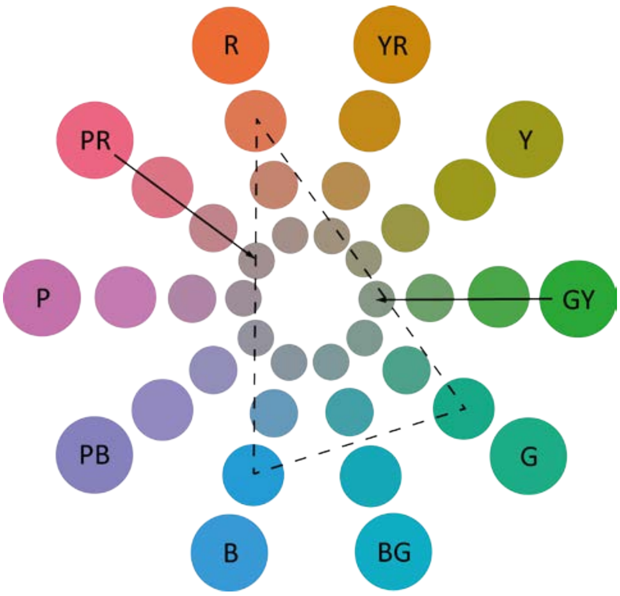


Fig.4 *Uniformly distributed color hues and saturations allow for calculations with colors.*

VI. Drawing Compelling Visualizations of Communication Networks

We have now discussed the basic concepts of visualizing communication networks, although there are many more approaches to be considered. Nonetheless, even as the methods become more complex, it is essential to know the visualization fundaments and to think about these basic questions for drawing networks: What is the information that you want to visualize? How is it possible to represent this information in a reasonable way? The visual elements should be used to render an intentional mapping of information as well as data. According to Tufte [14], information visualization should show the data, induce the viewer to think about the substance rather than the methodology, avoid distorting what the data have to say, and present many numbers in a small space, all while communicating with clarity and precision.

The number of available visual elements is very limited. Nonetheless, using these elements wisely can result in rich multivariate visualizations. For the mapping process, you can use the introduced design elements to add quantitative, nominal, and ordinal data to your picture. Applying the visual elements to graphical objects other than nodes (e.g., links, labels), offers even more opportunities to visualize information. When visual elements are used, they need to be closely integrated with cognitive assumptions about the data because, in many contexts, colors and shapes have real-world interpretations. For instance, companies that have negative profit are conventionally drawn red rather than green, political parties are normally connected to colors, and social scientists have agreed on using triangles and circles to draw women and men. Violating these predefined cognitive associations creates confusion and makes it harder to focus on the information in the network visualization.

Last but not least, as network nodes are often drawn with different sized shapes to represent quantitative information like revenue or centrality scores, there are two more things to consider. First, these scores and measures are one-dimensional information (i.e., one value for every node), while boxes and circles are two-dimensional objects. One of Tufte's [14] visualization rules tells us that the dimension of data should be consistent with the dimension of the graphical representation. This is why you can sometimes find network pictures that use two variables for the node size such as the width of the rectangle for the revenue and the height for the profit. Despite the fact that using just one variable to define shape sizes is redundant, it is acceptable from an aesthetic point of view. Secondly, humans are not very good at comparing different sized two- and three-dimensional objects. Stevens [12] defined a "psychophysical power law" that describes the difference between the perceived and actual magnitudes of an observed stimulus. In other words, when you experience two different sized objects, two different loud noises, smells, tastes or touches, you are not capable of correctly describing the actual differences between these stimuli. Lodge [8] empirically tested many of these impressions and came up with a perceived exponential margin of error of 0.7 for visual areas. To understand this number, take a look at the purple squares in Figure 5. The larger has exactly twice the area of the smaller, but human perception fails and, on average, causes us to think that the larger square is just 1.7 times larger. In contrast, the green squares represent a perceived size factor of 2.0 while it is actually 2.69. Consequently, to "correctly" represent size differences in network nodes, we need to take these numbers into account when calculating the size of drawn objects.

Fig.5 *Steven's psychophysical power law and it's implication to perceived (left: 1.7, right 2.0) and actual (left: 2.0, right: 2.69) size differences.*

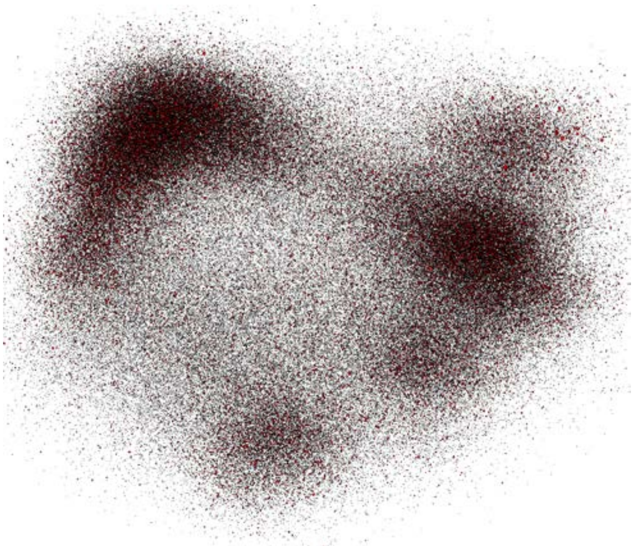
VII. FUTURE CHALLENGES

In this article, we have addressed principles for visualizing communication networks. As you can see, these principles are well known and discuss widely in literature. Although, when you look at pictures of communication networks in research articles or non-scientific publications, you will see that many violate these principles and create puzzling – and also unattractive – visualizations. To better incorporate aspects of perception is a challenge for researchers and information visualizer who draw communication networks, but also for developers of network analytical software. A large array of software tools, that you can use to analyze and visualize your network data, has been developed in recent years, four of which are widely used in the scientific community: Pajek, UciNet, Visone, and ORA. An extensive and updated list of tools can be found on the related Wikipedia page[3].

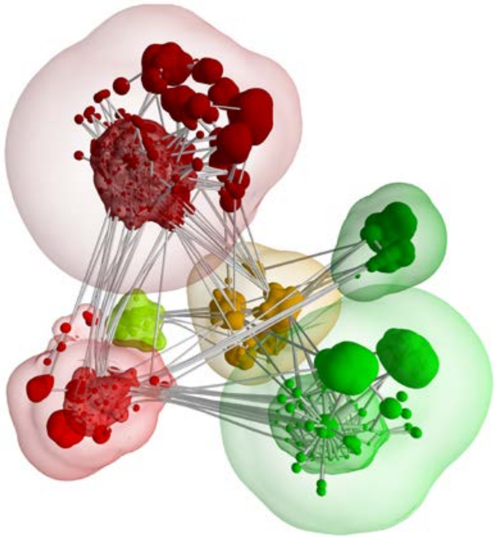
The main two question in the context of analyzing and visualizing communication networks are "Who is important?" and "Where are the groups?" Future challenges for visually reasoning about these questions arise from the availability of big and dynamic communication network data. Figure 6(a) shows the telephone communication network of approximately one million people. The layout was calculated on a single computer in less than one minute with the algorithm by Brandes and Pich [3]. For readability, links are not drawn and the majority of the nodes are sketched with black dots. What we can see (or hope to see) in pictures of big networks are structural patterns. Here, five highly concentrated clusters. Creating visualization algorithms that better support visual exploration of the structure in a reasonable time is one of the main challenges with respect to big networks.

In case community structures or hierarchical clusters are known a priori (e.g., geographical clusters) or pre-calculated with clustering algorithms, the challenge is to visualize these communities. Balzer and Deussen [1] developed a *level-of-detail* technique that simplifies the visualization to abstract representations of communities and that offers more and more details when the focus is on a specific part of the network, see Figure 6(b). This helps to reduce the visual complexity of big networks.

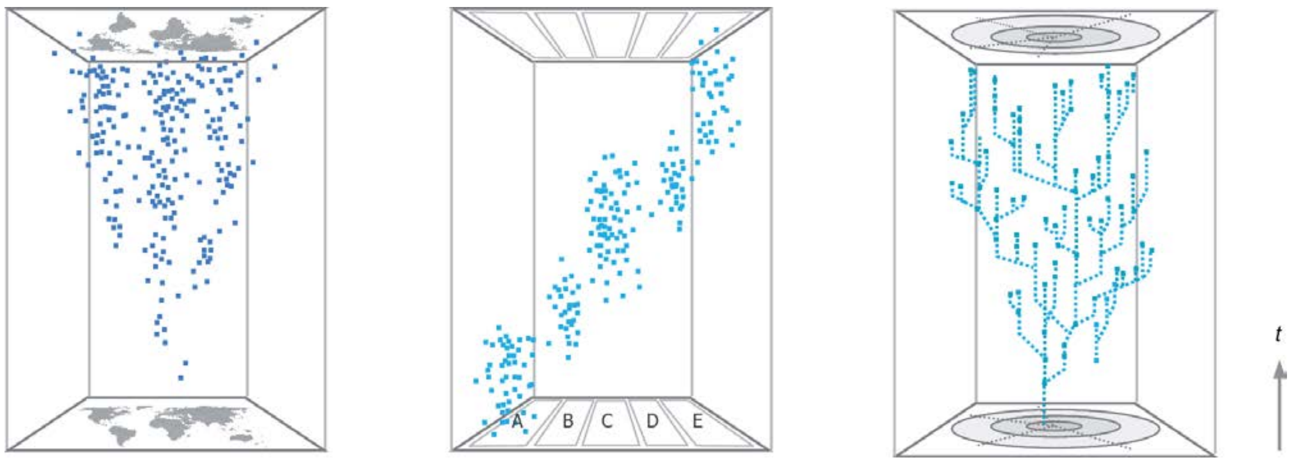
Another challenge is related to the *richness* of communication data. Phone logs or social media data come with time stamps, and often with geographical information. Incorporating the geographical aspects and temporal dynamics of these data requires new algorithms and interactive tools that support visual reasoning. Figure 6(c) shows the *Cultural Heritage Cube* from Windhager and Mayr [16] for which they extended visualization methods from time geography to an interactive visual framework that can be used, for instance, to explore exhibitions of



(a) *Visualizing big networks*



(b) *Visualizing and analyzing communities. Source: Balzer and Deussen (2006), used with permission.*



(c) *Visualizing networks in time and space. Source: Windhager and Mayr (2012), used with permission.*

Fig.6 *Future challenges for visualizing communication networks.*

museums.

In a nutshell, drawing compelling visualizations of communication networks is no mysterious feat, but the result of deliberate techniques. Beyond all the methods and tricks, however, they should always tell a story and answer questions, placing importance on information and not just data.

Note

1. Source: www.theyrule.net, used with permission. Revenues and profits (year 2003) are gathered from www.cnnmoney.com.
2. “That I am the only person in this century who has the right insight into the difficult science of colors, that is what I am rather proud of, and that is what gives me the feeling that I have outstripped many.” (Goethe, 1810).
3. http://en.wikipedia.org/wiki/Social_network_analysis_software

References

[1] BALZER M, DEUSSEN O. 2007. Level-of-detail visualization of clustered graph layouts, Asia-Pacific Symposium on Visualization (APVIS).

[2] BERTIN J. 1983. Semiology of Graphics: Diagrams, Networks, Maps, University of Wisconsin Press.

[3] BRANDES U, PICH C. 2007. Eigensolver Methods for Progressive Multidimensional Scaling of Large Data, in: M. Kaufmann, D. Wagner, Eds. Proceedings Graph Drawing: 42-53.

[4] FREEMAN LC. 2000. Visualizing social networks. Journal of Social Structure 1 (1).

[5] FRUCHTERMAN T, REINGOLD E. 1991. Graph Drawing by Force-Directed Placement, in: Software–Practice and Experience, vol. 21, no. 11: 1129-1164.

[6] HENNIG M, BRANDES U, PFEFFER J, MERGEL I. 2012. Studying Social Networks, Compas Verlag, Frankfurt.

[7] KAMADA T, KAWAI S. 1989. An Algorithm for Drawing General Undirected Graphs, in: Information Processing Letters, vol. 31: 7-15.

[8] LODGE M. 1981. Magnitude scaling, quantitative measurement of opinions, Sage Publications, Thousand Oaks, CA.

[9] MACKINLAY J. 1986. Automating the design of graphical presentations of relational information, in: ACM Trans. Graph. 5, 2 (Apr. 1986): 110-141.

[10] MORENO JL. 1953. Who Shall Survive? Foundations of Sociometry, Group Psychotherapy and Sociodrama. Originally published in 1934, Beacon House, New York.

[11] MUNSELL, AH. (January 1912). A Pigment Color System and Notation. The American Journal of Psychology 23 (2): 236–244.

[12] STEVENS S.S. 1975. Psychophysics: Introduction to Its Perceptual, Neural, and Social Prospects, Transaction Publishers.

[13] TORGERSON WS. 1952. Multidimensional scaling, in: Theory and Method. Psychometrika 17: 401-419.

[14] TUFTE ER, 2001. Visual Display of Quantitative Information, Second Edition, Graphics Press, Conneticut.

[15] WASSERMAN S, FAUST K. 1994. Social Network Analysis: Methods and Applications.: Cambridge University Press, Cambridge, MA.

[16] WINDHAGER F, MAYR E. 2012. Cultural Heritage Cube. A conceptual framework for visual exhibition exploration. Proceedings of the 16th International Conference on Information Visualisation (IV 2012).