Analyse Visuelle de Réseaux Sociaux Historiques: Traçabilité, Exploration et Analyse

Visual Analytics for Historical Social Networks: Traceability, Exploration, and Analysis

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Résumé:

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Abstract:

Historical Social Network Analysis is a method followed by social historians to model relational phenomena of the past such as kinship, political power, migrations, or business affiliations with networks using the content of historical documents. Through visualization and analytical methods, social historians are able to describe the global structure of such phenomena and explain individual behaviors through their network position. However, the inspection, encoding, and modeling process of the historical documents leading to a finalized network is complicated and often results in inconsistencies, errors, distortions, and traceability issues. For these reasons and usability issues, social historians are often not able to make thorough historical conclusions with current visualization tools. In this thesis, I aim to identify how visual analytics—the combination of data mining capabilities integrated into visual interfaces—can support social historians in their process, from the collection of their data to the answer to high-level historical questions. Towards this goal, I first formalize the workflow of historical network analysis in collaboration with social historians, from the acquisition of their sources to their final visual analysis, and propose to model historical sources into bipartite multivariate dynamic social networks with roles to satisfy traceability, simplicity, and document reality properties. This modeling allows a concrete representation of historical documents, hence letting users encode, correct, and analyze their data with the same abstraction and tools. I, therefore, propose two interactive visual interfaces to manipulate, explore, and analyze this type of data with a focus on usability for social historians. First, I present ComBiNet, which allows an interactive exploration leveraging the structure, time, localization, and attributes of the data model with the help of coordinated views, a visual query system, and comparison mechanisms. Finding specific patterns easily, social historians are able to find inconsistencies in their data and answer their questions. The second system, PK-Clustering, is a concrete proposition to increase the usability and effectiveness of clustering mechanisms in social network visual analytics systems. It consists in a mixed-initiative clustering interface that let social scientists create meaningful clusters with the help of their prior knowledge, algorithmic consensus, and exploration of the network. Both systems have been designed with continuous feedback from social historians, and aim to increase the traceability, simplicity, and document reality of the historical social network analysis process. I conclude with discussions on the potential merging of both systems and more globally on research directions towards better integration of visual analytics systems on the whole workflow of social historians. Such systems with a focus on usability can lower the requirements for the use of quantitative methods for historians and social scientists, which has always been a controversial discussion among practitioners.

Contents

1 Introduction

The goal of this thesis is to characterize and produce visual analytics tools that can support social historians conducting research on their sources—particularly when using network methods—with a focus on exploration, analysis, and traceability. Historical Social Network Analysis (HSNA) is a method—sometimes referred as a paradigm [?]—followed by social historians to study sociological phenomena through the observation of relationships of actors of the past, modeled into a network. The usage of networks as an abstraction to represent and study social relationships—such as friendships, kinship, or business ties—grew in popularity in the last 40 years [43, 138] and constitute a powerful metaphor, especially in our time when many of our digital connections and interactions use an explicit network structure[1]. This approach has first been formalized in sociology under the term Social Network Analysis (SNA) [43] and is now widely used in anthropology, geography, and history [72]. Historians leverage historical documents—which are at the core of their profession [?]—to extract relationships between actors of interest that they model with networks constructed from nodes and links that respectively represent actors (often persons) and relationships (like kinship). Using social network visualization techniques and leveraging network measures and computations, they can then test hypotheses they have and gain insight on the structural aspect of the relational phenomena they are studying [72,149]. This approach has been followed successfully to study various subjects such as kinship [59], entrepreneurship [121], maritime routes [78], political power [105], political oppositions [104], and persecution [?]. Yet, history is considered by many as a literary and qualitative science, and many critics emerged from the history community concerning quantitative and network methods [56,70,80,83], pointing to problems such as the leading to trivial conclusions, anachronisms, simplifications, and mismatches between network and historical concepts. Moreover, quantitative and network analysis are complex processes, and demand many efforts in data collection, encoding, modification, and processing before being able to make efficient observations. This thesis considers the whole workflow of social historians to better support it with visual analytics.

Social historians have to take many annotation (sometimes called encoding) and modeling decisions, concerning *what* to model from their sources into a network, and *how* to model it [23, 33], i.e., should the information of interest be represented as a node, a link, an attribute, or not reflected in the network at all, and what format should be used. Practically, they usually use ad hoc processing and analysis scripts to transform historical documents to analyzable networks, which is time-consuming, sometimes to end up with trivial or hard to interpret

[1] This analogy goes to the point that the term "Social Network" can refer both to the sociological metaphor for social relationship and the social media platforms such as Facebook.

results [2]. Still, HSNA led to many highly regarded studies with thorough conclusions, such as the study of families of power in Florence by Padgett and Ansell where they explained the rise of the Medici family through its central position in the economical, political, and trading networks of powerful families [105] or Gribaudi and Blum work on the social and professional shift during the 19th century in France [55].

The usage of visualization to graphically display networks is common in SNA[2] as it allows to unfold the structure of networks to the eyes, thus letting social scientists confirm hypotheses they had when collecting and exploring their data as well as gaining new insight through the discovery of interesting patterns and trends [24]. Images of networks also constitute an efficient mean of communication, especially in scientific productions [42]. Many visualization techniques and softwares have thus been developed since the birth of SNA, but most popular tools are usually not designed for historians specifically, meaning that they do not regard on the provenance and process leading to the network, and focus on analysis aspects only. Moreover, they usually enforce simple network models without proposing exploration mechanisms, beyond allowing to look at the network structure and computed measures. In result, many HSNA studies show a plot of their network and describe it qualitatively, often by identifying the central actors—sometimes with the help of centrality—but do not go beyond that [81]. *In this thesis, I therefore investigate how visualization can support social historians in their work, first during the pre-analysis process and secondly during the analysis step, with the right level of expressiveness, usability, and traceability.*

1.1 Social History and Historical Social Network Analysis

Social History has continuously evolved since its beginning in the 1930s, especially with the rise of quantitative and network methods based on the development of computer science during the end of the 20th century. If these computer-supported methods are now widely used in history [72, 109], they attracted many criticism from the start—some are which still relevant.

We can trace back the birth of Social History with the formation of the "Annales School" in the 1930s, where historians gained interest in socio-economic questions and started to rely heavily on the exhaustive extraction and analysis of historical documents coming from archives [10, 113]. Beforehand, History was mainly political and event-centered, as the majority of work consisted in narrating and characterizing specific events—such as wars and diplomatic alliances—while eliciting their causes and consequences, and describing the lives of historic figures,

[2]Historians and sociologists following network analyses typically use similar techniques and tools for analyzing their data. The difference between SNA and HSNA hence come from the provenance and process leading to the construction of the network. I therefore use the SNA acronym for practices common in both fields and the HSNA acronym for history specificities.

such as sovereigns [113]. Social History shifted the focus by aiming to link together sociological, economical, and political issues and by placing individuals at the center of these questions [?]. Later on in the 1960s, with the development of computer science, historians started to use quantitative methods to analyze data extracted from historical documents and make conclusions grounded in statistical results, in various subjects such as demographics [63] and economics [52]. Around the same time, the use and study of networks started to become popular in various disciplines to study real-world relational phenomena based on mathematical computations and measures, especially in sociology and anthropology [?]. A network is an abstraction based on graph theory concepts which can be used to model phenomena based on relationships (called links) between entities (called nodes).

Sociologists appropriated this concept to model social relationships between agents of interest, allowing them to study the sociological structure of groups of interest—such as families, institutions, and companies—and concepts like friendship, oppression, and diffusion using real world observation and mathematical computations. This SNA approach allows analysts to ground results in formal network measures and metrics based on real observations instead of relying on traditional social categories such as age, job, and gender [43]. This shift in the object of study from traditional social classes and aggregates to the observation of relationships of individuals remind the microhistory movement [49] which theorized that following the life of single individuals and small groups enable the making of higher level conclusions about the social structures they live in. Social historians followed this tradition and started to appropriate network concepts to study relational aspects of the past and formalized it under the term Historical Network Research or Historical Social Network Analysis [149]. However, historians do not have the possibility to run surveys or directly observe interactions of the past and are thus constrained by the information contained in historical documents they find in archives. These documents can be anything mentioning social relationships between actors of interest, such as marriage acts, birth certificates, census, migration acts, business transactions, journals. After selecting a corpus of documents, they typically read and inspect in depth several documents while taking notes to have a deeper insight on the content of the sources, which allow them to start eliciting hypotheses. Following this exploration phase, they manually annotate each document and encode the desired information—the mention of persons and their social relationship in the case of a network analysis. This is a long and tedious process that can result in small to large networks that they analyze using network measures to make conclusions on the structure of social groups or social behaviour of individual of interests. Figure 1.1 shows for example an original business document of the 17th century from Nantes (France). The historian have to inspect these documents in depth, extract useful information, and cross-reference the sources to do her quantitative analysis afterwards.

The investigation and reading of the historical documents is therefore an ex-

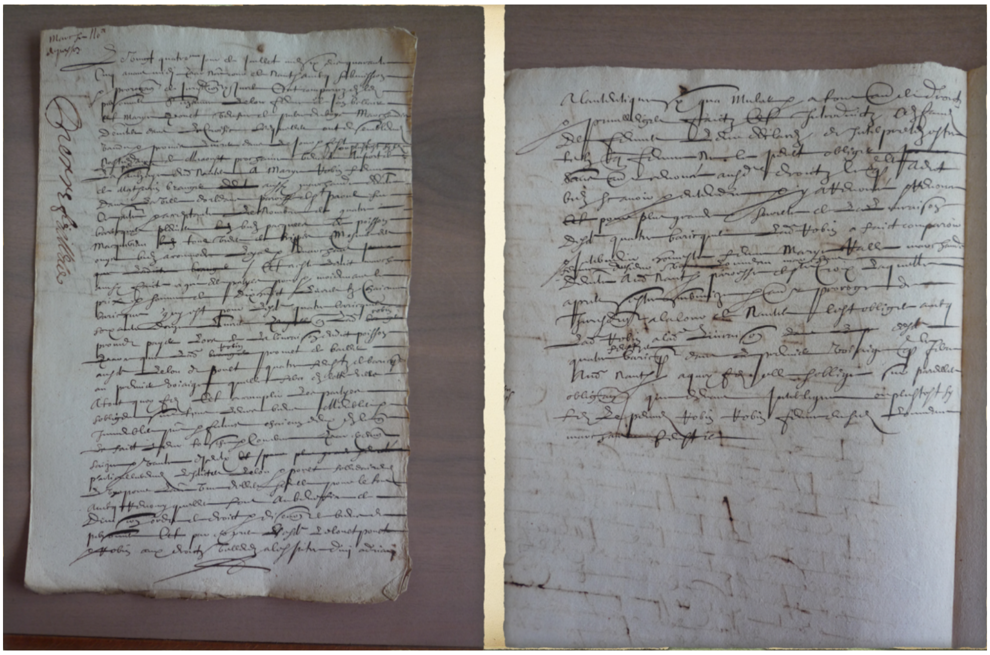

Figure 1.1 – Business contract originated from Nantes (France) during the 17th century. See [34] for more detail of the historian process to analyze her sources.

ploratory process, where historians start to generate sociological hypotheses from the continuous extraction of insight and revelations of this process, similarly to grounded theory [50]. Once they finalised a network, they can test their hypotheses using qualitative or quantitative methods—based on statistical and network measures. Lemercier and Zalc write "Although history is not an exact science, counting, comparing, classifying, and modeling are nevertheless useful methods for measuring our degree of doubt or certainty, making our hypotheses explicit, and evaluating the influence of a phenomenon." [81] Social historians, therefore, have hypotheses about their subject of study, that they can back up or refute with the help of quantitative and network results, in a way similar to the competing hypotheses workflow of Intelligence Analysis [30]. By pointing to evidence supporting or refuting hypotheses, they can give insight into the level of the plausibility of different claims.

1.2 Visualization and Visual Analytics

Visualization has been said to be a central part in the development of SNA [?, 42]—as it the case for many scientific fields[3]. Social scientists now widely

[3]the historian Alfred Crosby went as far as claiming that visualization is one of the two factors—with measurement—which led to the development of modern science

use visual and analytical tools to unfold their network structure, allowing them to confirm or deny hypotheses, or follow exploration analysis.

Visualization is the process of displaying data visually to leverage the human visual system and enhance cognition to gain insight into data [19]. Using visual abstractions (such as size, color, and position) to display abstract data allows us to rapidly see structure and patterns otherwise hidden in raw text and numbers. As data keeps growing in size with time due to the increase of hardware and storage capabilities, visualization is a powerful tool to gain insight into the underlying structure of various complex datasets.

Visualization has traditionally been used for confirmatory and communication purposes, particularly in empirical sciences [?]. By showing data visually, analysts are able to confirm or refute hypotheses and communicate their findings in scientific productions.

However, visualization can also be used for exploration, which can help to understand the underlying structure of data and generate new hypotheses. Tukey defined this process as Exploratory Data Analysis in the 1960s [141], as a procedure to gain insight into the structure of the data by identifying outliers, trends, and patterns with the usage of visualization and statistical measures. Social network visualization is used for communication of findings in the field, but is also often following this exploration process as showing the network visually allows social scientists to reveal the structure of their data. As freeman writes "Images of social networks have provided investigators with new insights about network structures and have helped them to communicate those insights to others" [42]. Social scientists very often represent their data using node-link diagrams, that we find in every production of reference in the field [79, 138, 148].

Figure 1.2 shows a node-link representation of the network constructed by Padgett and Ancell in their work on the Medici. At that time, diagrams were often drawn by hand, practice which have now been replaced by automatic layout algorithms.

Most visual software for SNA such as Gephi [5], Pajek [106], NodeXl [133], or Ucinet [?] are based on this representation, and allow an exploration of the data with the help of basic interaction mechanisms and the computation of network measures.

The detection of patterns and trends can also be facilitated with automatic methods coming from data mining and machine learning fields, directly implemented in the visual analysis loop. This coupling of visual exploration and automatic data mining algorithms has been coined as Visual Analytics (VA) and is defined as the process of using interactive visualizations, transformations, and models of the data in an interactive analysis workflow to create knowledge [71].

[?]

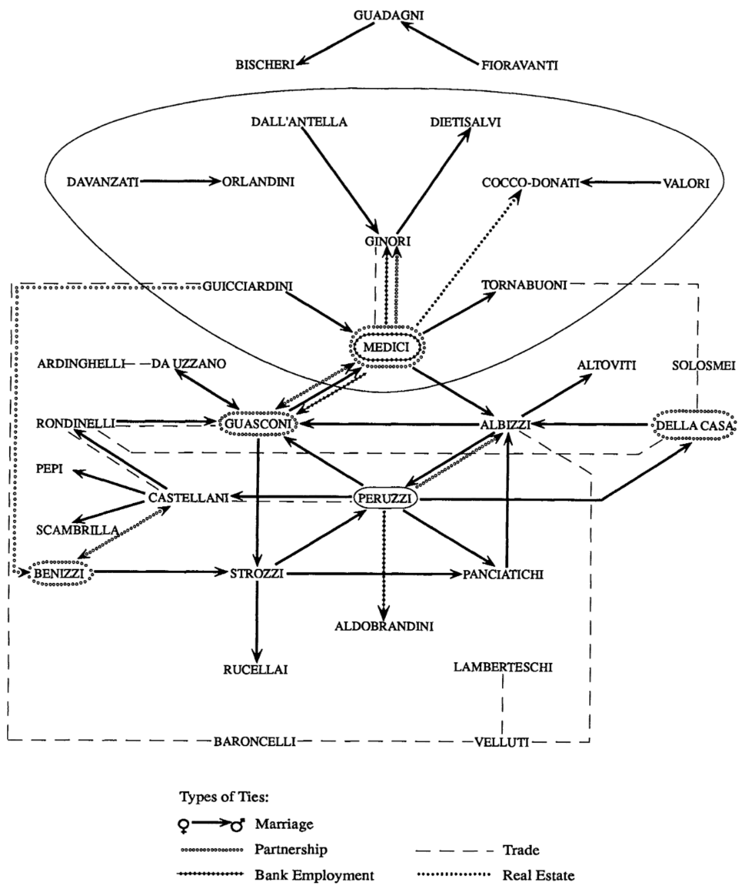

Figure 1.2 – Marriage, partnership, trading, banking, and real estate networks of the powerful families of Florence from [105]. We can see the central position in the network of the Medici Family.

Figure 1.3 illustrate the schematic process of VA: the coupling of visualization and data mining models operated by the user through interaction lead to the generation of knowledge "extracted" from the data.

If most widely used visual interface for HSNA do not yet provide complex interactions or high data mining capabilities, more recent tools are oriented towards VA, as the combination of automatic knowledge extraction with interaction and exploration can be a powerful support for social scientists to gain insight on the structure of their network, especially that the data they study keep growing in size and complexity [69].

1.3 Visual Analytics Supported Historical Network Research

Most visual tools for SNA are designed for the analysis of already curated networks, without taking into account the context in which those networks have

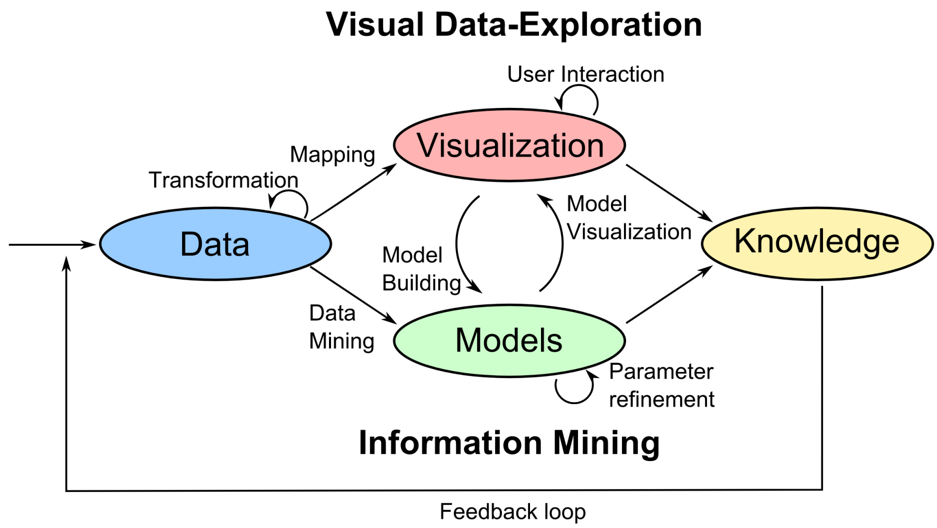

Figure 1.3 – Abstraction of the VA process. It is characterized by continuous interactions between the data, visualizations, models, and knowledge. Image from [71].

been produced, where they come from, and the workflow that led to their creation. Moreover, many practitioners have trouble using current computer-supported tools, due to misconception in their encoding and modeling process or usability problems. VA should therefore support social historians in the entirety of their process, with a focus on usability and simplicity.

Currently, social historians spend a lot of time in their data acquisition, processing, and encoding steps which lead them to the construction of a network [34, 82]. They typically visualize and analyze their network at the end of this process, first to verify hypotheses they formulated during the inspection of their sources, then to gain a better view of the structure of the network, allowing them to potentially generate new hypotheses [80]. However, research showed that all the steps preceding the analysis can introduce errors and misconceptions, especially since social scientists are often not trained in computer science and data science [2, 81]. Social scientists usually visualize their network using SNA tools like Gephi, Pajek, and NodeXl which encompass basic interactions, node-link visualization, SNA measure computations, and clustering algorithms. Once they visualize their data, they typically notice errors and inconsistencies in the data, such as duplication of the same entities, merging of different entities, or geolocation errors [2, 31].

Practitionners also have to decide on a network model [23] (see §2.3.4 for more details) when encoding their documents, which sometimes do not match the final analysis goals. Simple models typically oversimplify the relationships contained in the sources [80] and too complicated models are hard to manipulate [?]. They, therefore, have to go back and forth between the visualization software and the encoding process which can be tedious, especially since it can be complicated to trace back the entities of the data model back to the original documents for correction. VA tools that encompass the whole process of social historians should therefore be beneficial for the flow of their work and could help detect and correct errors or analysis plans way before the visualization of a finalised network.

Furthermore, several historians highlighted the fact that many social history studies leveraging network methods simply use networks in a metaphorical sense, in what Rollinger calls "soft SNA" or "informal network research" [?]. Such studies typically show one—or a couple—node-link diagram(s) of their data, which they describe with qualitative terms [81] to refer to the global structure of the network (dense, parse, connected, etc.), the place of actors (central, distant), or interesting patterns (cliques, bridges, communities). In case of dense networks, such descriptions become obsolete, as diagrams start to look like what have been called a "spaghetti monster" [?, 81] i.e., an unreadable image due to the high level of cluttering. Figure 1.4 shows for example a medieval social network of peasants proximity relationships between 1250 and 1350 extracted from agrarian contracts. The graphic do not convey much information, especially that the links represent a constructed notion of proximity without indicating the types of relationships the individuals were mentioned in the contracts.

The lack of usage of network analytical methods—which are numerous in modern SNA softwares[4]—have been in part explained by "math anxiety" [?]: it takes long effort to learn the mathematical concepts behind network measures and algorithms, and their relationships to sociological concepts [?], especially for practitioners without formal computer science and mathematical training. My claim is that current HSNA tools do not support social scientists enough in their analysis due to 1) the lack of interaction, direct manipulation, and exploration mechanisms in current interfaces and 2) the lack of network measures and algorithm interpretations and explainability. For example, clustering algorithms are often included in such systems, letting social scientists partition networks into groups, but many algorithms exist in the literature, potentially giving diverse results. Scientists often run several algorithms until finding a satisfying enough partition, which can bias the result of an analysis [?]. Usability and traceability of the results are therefore primordial in VA interfaces aimed at supporting social historians in their analysis.

VA could therefore help social historians using network methods for their research, first by supporting their entire workflow to help them explore, encode, correct, and model their data with simple tools and without introducing oversimplifications, but also to provide guidance and exploration mechanisms during the purely analytical step. For this, such interfaces should therefore 1) be simple enough to manipulate, 2) model the original documents and annotations without distortions, and 3) let historians trace back their network entities to the original sources and analytical results in explainable frameworks. In other terms, they

[4] See for example the long technical manuals of Pajek [106] or Ucinet [?]

Figure 1.4 – Node-link diagram of a medieval social network of peasants, produced with a force-directed layout, commonly used in SNA softwares. Image from [**?**].

should satisfy *simplicity*, *document reality*, and *traceability* principles. We discuss and explain them more in depth in chapter 3.

1.4 Contributions and Research Statement

The goal of this thesis is to characterize how VA can support social historians in their HSNA process and present proofs of concepts of tools supporting it. Most social network visualization tools are agnostic to the process of social historians leading to a polished network, even though it has an high impact of the network model and structure. Using visualization only at the end of the process often reveals potential errors, inconsistencies, or mismatches between the network model and analysis goals [2]. Moreover, due to lack of usability and interaction mechanisms, social historians often simply visualize statically their network and partially describe their structure, leading to conclusion which would have been easier to reach with simpler methods [39].

VA could therefore 1) assist social historians in their overall workflow, starting at the documents' acquisition to the final analysis step, with the help of data mining and interaction mechanisms in the data acquisition, encoding, modeling steps, and 2) provide exploration and analysis mechanisms to answer complex historical questions, beyond simply plotting the network with a node-link diagram.

The goal of this thesis is hence to give answers to the high-level question "How can VA support social historians in their entire HSNA process?". To answer this question, I first characterize the HSNA process from start to finish from discussions and collaborations with social historians, with the goal of identifying pitfalls that regularly arise and characterizing social historians' needs. From this, I give answers and directions—illustrated by proof-of-concepts—to three questions concerning the modeling aspect of HSNA and how VA and automatic tools can support social historians in different parts of their process:

Q1: How to model historical documents into an analyzable network with the right balance between expressiveness and simplicity?

Q2: What representations and interactions would allow social historians answer complex historical questions—with a focus on usability ?

Q3: How to design VA tools and interactions that leverage algorithmic power but keep historians in control of their analyses and biases?

In chapter 3, I start by describing the HSNA workflow and identify recurring pitfalls we encountered in our collaborations with historians and answer **Q1** by proposing a network model for modeling historical documents. In the following chapter 4, I give answers to **Q2** by providing a VA interface to explore bipartite multivariate dynamic networks, with queries and comparison interactions with the aim of letting historians find errors easily, transform their network data, answer their questions, and generate interesting hypotheses. Finally, in chapter 5, I propose PK-Clustering, a mixed-initiative clustering technique for social scientists based on their prior knowledge, algorithmic consensus, and traceability of results, as a concrete example of a system providing answers to **Q3**.

Bibliography

[1] NodeXL: Simple network analysis for social media.

[2] Mashael Alkadi, Vanessa Serrano, James Scott-Brown, Catherine Plaisant, Jean-Daniel Fekete, Uta Hinrichs, and Benjamin Bach. Understanding barriers to network exploration with visualization: A report from the trenches. *IEEE Transactions on Visualization and Computer Graphics*, 27(2), 2022. 12, 17, 19, 21, 37, 41, 43, 44, 46, 49, 58

[3] Keith Andrews, Martin Wohlfahrt, and Gerhard Wurzinger. Visual Graph Comparison. In *2009 13th International Conference Information Visualisation*, pages 62–67, July 2009. 65

[4] F. J. Anscombe. Graphs in Statistical Analysis. *The American Statistician*, 27(1):17–21, February 1973. 22, 24

[5] Mathieu Bastian, Sebastien Heymann, and Mathieu Jacomy. Gephi: An open source software for exploring and manipulating networks. In Eytan Adar, Matthew Hurst, Tim Finin, Natalie S. Glance, Nicolas Nicolov, and Belle L. Tseng, editors, *ICWSM*. The AAAI Press, 2009. 15, 40, 62, 71, 93

[6] Sugato Basu, Ian Davidson, and Kiri Wagstaff. *Constrained Clustering: Advances in Algorithms, Theory, and Applications*. Chapman & Hall/CRC, first edition, 2008. 97

[7] Leilani Battle and Jeffrey Heer. Characterizing Exploratory Visual Analysis: A Literature Review and Evaluation of Analytic Provenance in Tableau. *Computer Graphics Forum*, 38(3):145–159, 2019. 65

[8] Jacques Bertin. *Sémiologie graphique: les diagrammes, les réseaux, les cartes*. Paris: Gauthier-Villars, 1967. 22, 23

[9] A. Bezerianos, F. Chevalier, P. Dragicevic, N. Elmqvist, and J.d. Fekete. GraphDice: A System for Exploring Multivariate Social Networks. *Computer Graphics Forum*, 29(3):863–872, 2010. 72

[10] Marc Bloch. *Apologie Pour l'histoire*. A. Colin, 1949. 12

[11] Christian Böhm and Claudia Plant. HISSCLU: A hierarchical density-based method for semi-supervised clustering. In *Proceedings of the 11th International Conference on Extending Database Technology: Advances in Database Technology*, EDBT '08, pages 440–451, New York, NY, USA, 2008. ACM. 97

[12] Christian Bors, John Wenskovitch, Michelle Dowling, Simon Attfield, Leilani Battle, Alex Endert, Olga Kulyk, and Robert S. Laramee. A Provenance Task Abstraction Framework. *IEEE Computer Graphics and Applications*, 39(6):46–60, November 2019. 65

[13] Michael Bostock, Vadim Ogievetsky, and Jeffrey Heer. D^3 Data-Driven Documents. *IEEE Transactions on Visualization and Computer Graphics*, 17(12):2301–2309, December 2011. 71, 82

[14] Pierre Bourdieu. Sur les rapports entre la sociologie et l'histoire en Allemagne et en France. *Actes de la Recherche en Sciences Sociales*, 106(1):108–122, 1995. 27

[15] Ulrik Brandes, Daniel Delling, Marco Gaertler, Robert Gorke, Martin Hoefer, Zoran Nikoloski, and Dorothea Wagner. On Modularity Clustering. *IEEE Transactions on Knowledge and Data Engineering*, 20(2):172–188, February 2008. 49

[16] Peter Burke. *History and Social Theory*. Polity, 2005. 27

[17] Steven P. Callahan, Juliana Freire, Emanuele Santos, Carlos E. Scheidegger, Cláudio T. Silva, and Huy T. Vo. VisTrails: Visualization meets data management. In *Proceedings of the 2006 ACM SIGMOD International Conference on Management of Data - SIGMOD '06*, page 745, Chicago, IL, USA, 2006. ACM Press. 65

[18] Charles-Olivier Carbonell. *L'Historiographie*. FeniXX, January 1981. 27

[19] Stuart-K. Card, Jock-D. Mackinlay, and Ben Shneiderman. *Readings in Information Visualization: Using Vision to Think*. Morgan Kaufmann Publishers In, San Francisco, Calif, February 1999. 15, 22

[20] Duen Horng Chau, Christos Faloutsos, Hanghang Tong, Jason I. Hong, Brian Gallagher, and Tina Eliassi-Rad. GRAPHITE: A Visual Query System for Large Graphs. In *2008 IEEE International Conference on Data Mining Workshops*, pages 963–966, December 2008. 64

[21] J. S. Coleman. Introduction to mathematical sociology. *Introduction to mathematical sociology.*, 1964. 33

[22] TEI Consortium. TEI P5: Guidelines for electronic text encoding and interchange, February 2021. 48

[23] Pascal Cristofoli. Aux sources des grands réseaux d'interactions. *Reseaux*, 152(6):21–58, 2008. 11, 17, 35, 44, 46, 49, 55, 62

[24] Pascal Cristofoli. Principes et usages des dessins de réseaux en SHS. *La visualisation des données en histoire*, page 35, 2015. 12, 39, 71

[25] Pascal Cristofoli and Nicoletta Rolla. Temporalités à l'œuvre dans les chantiers du bâtiment. *Temporalités. Revue de sciences sociales et humaines*, (27), June 2018. 51, 54, 66, 71

[26] Tarik Crnovrsanin, Chris W. Muelder, Robert Faris, Diane Felmlee, and Kwan-Liu Ma. Visualization techniques for categorical analysis of social networks with multiple edge sets. *Social Networks*, 37:56–64, 2014. 51

[27] Gabor Csardi and Tamas Nepusz. The igraph software package for complex network research. *InterJournal*, Complex Systems:1695, 2006. 64, 71

[28] Erick Cuenca, Arnaud Sallaberry, Dino Ienco, and Pascal Poncelet. VERTIGo: A Visual Platform for Querying and Exploring Large Multilayer Networks. *IEEE Transactions on Visualization and Computer Graphics*, pages 1–1, 2021. 64, 91

[29] Zach Cutler, Kiran Gadhave, and Alexander Lex. Trrack: A Library for Provenance-Tracking in Web-Based Visualizations. In *2020 IEEE Visualization Conference (VIS)*, pages 116–120, October 2020. 79, 82

[30] Mandeep K. Dhami, Ian K. Belton, and David R. Mandel. The "analysis of competing hypotheses" in intelligence analysis. *Applied Cognitive Psychology*, 33(6):1080–1090, 2019. 14

[31] Jana Diesner, Craig Evans, and Jinseok Kim. Impact of Entity Disambiguation Errors on Social Network Properties. *Proceedings of the International AAAI Conference on Web and Social Media*, 9(1):81–90, 2015. 17, 42, 44, 48

[32] Dana Diminescu. The migration of ethnic germans from romania to west germany: Insights from the archives of the former communist regime. In *CERS, Public Lecture, UCLA*, Los Angeles, United States, March 2020. 54, 68

[33] Nicole Dufournaud. La recherche empirique en histoire à l'ère numérique. *Gazette des archives*, 240(4):397–407, 2015. 11

[34] Nicole Dufournaud. Comment rendre visible le rôle économique des femmes sous l'Ancien Régime ? Étude méthodologique sur les marchandes à Nantes aux XVIe et XVIIe siècles. In Bernard Michon and Nicole Dufournaud, editors, *Femmes et Négoce Dans Les Ports Européens (Fin Du Moyen Age - XIXe Siècle)*, pages 65–84. Peter Lang, 2018. 14, 17, 46, 50

[35] Nicole Dufournaud and Jean-Daniel Fekete. Comparaison d'outils pour la visualisation de sources historiques codées en XML/TEI. *Document numérique*, 9(2):37–56, April 2006. 48

[36] Cody Dunne, Nathalie Henry Riche, Bongshin Lee, Ronald Metoyer, and George Robertson. GraphTrail: Analyzing large multivariate, heterogeneous networks while supporting exploration history. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, CHI '12, pages 1663–1672, New York, NY, USA, May 2012. Association for Computing Machinery. 65

[37] P. Erdös and A. Rényi. On the evolution of random graphs. In *On the Evolution of Random Graphs*, pages 38–82. Princeton University Press, October 2011. 32

[38] Emily Erikson and Peter Bearman. Malfeasance and the Foundations for Global Trade: The Structure of English Trade in the East Indies, 1601–1833. *American Journal of Sociology*, 112(1):195–230, July 2006. 51

[39] Michael Eve. Deux traditions d'analyse des reseaux sociaux. *Réseaux*, 115(5):183–212, 2002. 20, 34, 35

[40] Lucien Febvre. VERS UNE AUTRE HISTOIRE. *Revue de Métaphysique et de Morale*, 54(3/4):225–247, 1949. 27

[41] Jean-Daniel Fekete, Danyel Fisher, Arnab Nandi, and Michael Sedlmair. *Progressive Data Analysis and Visualization*. Schloss Dagstuhl–Leibniz-Zentrum fuer Informatik, April 2019. 77

[42] L. Freeman. Visualizing Social Networks. *J. Soc. Struct.*, 2000. 12, 14, 15, 38

[43] L.C. Freeman. *The Development of Social Network Analysis: A Study in the Sociology of Science*. Empirical Press, 2004. 11, 13, 21, 31, 32, 33, 34, 49

[44] Manuel Freire, Catherine Plaisant, Ben Shneiderman, and Jen Golbeck. ManyNets: An interface for multiple network analysis and visualization. In *CHI '10*, CHI '10, pages 213–222, New York, NY, USA, 2010. ACM. 65

[45] Michael Friendly. Visions and Re-Visions of Charles Joseph Minard. *Journal of Educational and Behavioral Statistics*, 27(1):31–51, March 2002. 22

[46] Michael Friendly. A Brief History of Data Visualization. In Chun-houh Chen, Wolfgang Härdle, and Antony Unwin, editors, *Handbook of Data Visualization*, Springer Handbooks Comp.Statistics, pages 15–56. Springer, Berlin, Heidelberg, 2008. 22

[47] GEDCOM: The genealogy data standard. 37

[48] Mohammad Ghoniem, J.-D. Fekete, and Philippe Castagliola. A comparison of the readability of graphs using node-link and matrix-based representations. In *IEEE Symposium on Information Visualization*, pages 17–24. Ieee, 2004. 39

[49] Carlo Ginzburg and Carlo Poni. La micro-histoire. *Le Débat*, 17(10):133, 1981. 13, 35, 45

[50] Barney G. Glaser and Anselm L. Strauss. *The Discovery of Grounded Theory: Strategies for Qualitative Research*. Aldine Transaction, New Brunswick, 5. paperback print edition, 2010. 14

[51] Michael Gleicher. Considerations for visualizing comparison. *IEEE Trans. Vis. Comput. Graphics*, 24(1):413–423, 2018. 65

[52] Claudia Goldin. Cliometrics and the Nobel. *Journal of Economic Perspectives*, 9(2):191–208, June 1995. 13

[53] Martin Grandjean. Social network analysis and visualization: Moreno's Sociograms revisited, 2015. 32

[54] Martin Grandjean. Analisi e visualizzazioni delle reti in storia. L'esempio della cooperazione intellettuale della Società delle Nazioni. *ME*, (2/2017), 2017. 62

[55] Maurizio Gribaudi and Alain Blum. Des catégories aux liens individuels : l'analyse statistique de l'espace social. *Annales*, 45(6):1365–1402, 1990. 12

[56] Jo Guldi and David Armitage. *The History Manifesto*. Cambridge University Press, October 2014. 11

[57] Aric A. Hagberg, Daniel A. Schult, and Pieter J. Swart. Exploring network structure, dynamics, and function using NetworkX. In Gaël Varoquaux, Travis Vaught, and Jarrod Millman, editors, *Proceedings of the 7th Python in Science Conference*, pages 11–15, Pasadena, CA USA, 2008. 64, 93

[58] Klaus Hamberger, Cyril Grange, Michael Houseman, and Christian Momon. Scanning for patterns of relationship: Analyzing kinship and marriage networks with Puck 2.0. *The History of the Family*, 19(4):564–596, October 2014. 35, 38, 51

[59] Klaus Hamberger, Michael Houseman, and R. White, Douglas. Kinship network analysis. In John Scott & Peter J. Carrington, editor, *The Sage Handbook of Social Network Analysis*, pages 533–549. Sage Publications, 2011. 11, 37

[60] Mountaz Hascoët and Pierre Dragicevic. Interactive graph matching and visual comparison of graphs and clustered graphs. In Genny Tortora, Stefano Levialdi, and Maurizio Tucci, editors, *AVI '12*, pages 522–529. ACM, 2012. 65

[61] J. Heer and D. Boyd. Vizster: Visualizing online social networks. In *IEEE Symposium on Information Visualization, 2005. INFOVIS 2005.*, pages 32–39, October 2005. 73

[62] Jeffrey Heer. Agency plus automation: Designing artificial intelligence into interactive systems. *Proceedings of the National Academy of Sciences*, 116(6):1844–1850, 2019. 122

[63] Louis Henry and Michel Fleury. Des registres paroissiaux a l'histoire de la population: Manuel de dépouillement et d'exploitation de l'état civil ancien. *Population (French Edition)*, 11(1):142–144, 1956. 13

[64] Nathalie Henry, Jean-Daniel Fekete, and Michael J. McGuffin. NodeTrix: A Hybrid Visualization of Social Networks. *IEEE Transactions on Visualization and Computer Graphics*, 13(6):1302–1309, November 2007. 39, 40

[65] Aidan Hogan, Eva Blomqvist, Michael Cochez, Claudia D'amato, Gerard De Melo, Claudio Gutierrez, and Sabrina Kirrane et al. Knowledge graphs. *ACM Comput. Surv.*, 54(4), July 2021. 51

[66] Pat Hudson and Mina Ishizu. *History by Numbers: An Introduction to Quantitative Approaches*. Bloomsbury Publishing, November 2016.

[67] Infovis SC policies FAQ. 112

[68] Piers J Ingram, Michael PH Stumpf, and Jaroslav Stark. Network motifs: Structure does not determine function. *BMC Genomics*, 7:108, May 2006. 64

[69] Frédéric Kaplan. The Venice Time Machine. In *Proceedings of the 2015 ACM Symposium on Document Engineering*, DocEng '15, page 73, New York, NY, USA, September 2015. Association for Computing Machinery. 29

[70] Karine Karila-Cohen, Claire Lemercier, Isabelle Rosé, and Claire Zalc. Nouvelles cuisines de l'histoire quantitative. *Annales. Histoire, Sciences Sociales*, 73(4):773–783, December 2018. 11, 45, 46, 50

[71] Daniel Keim, Gennady Andrienko, Jean-Daniel Fekete, Carsten Görg, Jörn Kohlhammer, and Guy Melançon. Visual Analytics: Definition, Process, and Challenges. In Andreas Kerren, John T. Stasko, Jean-Daniel Fekete, and Chris North, editors, *Information Visualization: Human-Centered Issues and Perspectives*, Lecture Notes in Computer Science, pages 154–175. Springer, Berlin, Heidelberg, 2008. 15, 17, 25

[72] Florian Kerschbaumer, Linda von Keyserlingk-Rehbein, Martin Stark, and Marten Düring. *The Power of Networks. Prospects of Historical Network Research*. Routledge, December 2021. 11, 12, 21, 36

[73] Steffen Klamt, Utz-Uwe Haus, and Fabian Theis. Hypergraphs and cellular networks. *PLoS computational biology*, 5(5):e1000385, 2009. 90

[74] Elena V. Konstantinova and Vladimir A. Skorobogatov. Application of hypergraph theory in chemistry. *Discrete Mathematics*, 235(1-3):365–383, May 2001. 90

[75] C. Kosak, J. Marks, and S. Shieber. Automating the layout of network diagrams with specified visual organization. *IEEE Transactions on Systems, Man, and Cybernetics*, 24(3):440–454, March 1994. 39

[76] Ernest Labrousse. *La Crise de l'économie Française à La Fin de l'Ancien Régime et Au Début de La Révolution*, volume 1. Presses Universitaires de France-PUF, 1990. 27

[77] Charles-Victor Langlois and Charles Seignobos. *Introduction aux études historiques*. ENS Éditions, February 2014.

[78] Katherine A. Larson. Thomas F. Tartaron, Maritime Networks in the Mycenaean World. New York: Cambridge University Press, 2013. *Comparative Studies in Society and History*, 56(4):1064–1065, October 2014. 11

[79] Emmanuel Lazega. *Réseaux sociaux et structures relationnelles*. Presses universitaires de France, Paris, 1998. 15, 34

[80] Claire Lemercier. 12. Formal network methods in history: Why and how? In Georg Fertig, editor, *Social Networks, Political Institutions, and Rural Societies*, volume 11, pages 281–310. Brepols Publishers, Turnhout, January 2015. 11, 17, 21, 33, 35, 36, 37, 38, 41, 43, 52, 62

[81] Claire Lemercier and Claire Zalc. *Quantitative Methods in the Humanities: An Introduction*. University of Virginia Press, March 2019. 12, 14, 17, 18, 28, 29, 31, 38, 43, 45, 46, 62, 121

[82] Claire Lemercier and Claire Zalc. Back to the Sources: Practicing and Teaching Quantitative History in the 2020s. *Capitalism*, 2(2):473–508, 2021. 17, 28, 43, 44, 45, 46, 50

[83] Bernard Lepetit. L'histoire quantitative : deux ou trois choses que je sais d'elle. *Histoire & Mesure*, 4(3):191–199, 1989. 11, 45

[84] Carola Lipp. Kinship Networks, Local Government, and Elections in a Town in Southwest Germany, 1800-1850. *Journal of Family History*, 30(4):347–365, October 2005. 35

[85] Gribaudi Maurizio. *Espaces, Temporalités, Stratifications :. Exercices Méthodologiques Sur Les Réseaux Sociaux*. Editions de l'Ecole des Hautes Etudes en Sciences Sociales, Paris, January 2000. 34

[86] Philip Mayer. Migrancy and the Study of Africans in Towns. *American Anthropologist*, 64(3):576–592, 1962. 35

[87] Fintan McGee, Benjamin Renoust, Daniel Archambault, Mohammad Ghoniem, Andreas Kerren, and Bruno Pinaud et al. *Visual Analysis of Multilayer Networks*. Synthesis Lectures on Visualization. Morgan & Claypool Publishers, 2021. 51

[88] Michael J. McGuffin. Simple algorithms for network visualization: A tutorial. *Tsinghua Science and Technology*, 17(4):383–398, August 2012. 39

[89] Pierre Mercklé and Claire Zalc. Peut-on modéliser la persécution ?: Apports et limites des approches quantifiées sur le terrain de la Shoah. *Annales. Histoire, Sciences Sociales*, 73(4):923–957, December 2018.

[90] R. Michalski, P. Kazienko, and D. Krol. Predicting Social Network Measures Using Machine Learning Approach. In *2012 IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining*, pages 1056–1059, Istanbul, August 2012. IEEE. 122

[91] R. Milo, S. Shen-Orr, S. Itzkovitz, N. Kashtan, D. Chklovskii, and U. Alon. Network Motifs: Simple Building Blocks of Complex Networks. *Science*, 298(5594):824–827, October 2002. 34, 64

[92] Christoph Molnar. *Interpretable Machine Learning. A Guide for Making Black Box Models Explainable*. Lulu.com, 2019. 96

[93] Megan Monroe, Krist Wongsuphasawat, Catherine Plaisant, Ben Shneiderman, Jeff Millstein, and Sigfried Gold. Exploring point and interval event patterns: Display methods and interactive visual query. *University of Maryland Technical Report*, 2012. 89

[94] J. L. Moreno. *Who Shall Survive?: A New Approach to the Problem of Human Interrelations*. Who Shall Survive?: A New Approach to the Problem of Human Interrelations. Nervous and Mental Disease Publishing Co, Washington, DC, US, 1934. 32, 38

[95] J. L. Moreno. Foundations of Sociometry: An Introduction. *Sociometry*, 4(1):15, February 1941. 32, 51

[96] Zacarias Moutoukias. Buenos Aires, port between two oceans: Mobilities, networks, stratifications (2nd half of the 18th century). *E-SPANIA-REVUE ELECTRONIQUE D ETUDES HISPANIQUES MEDIEVALES*, 25, 2016. 54, 68

[97] Zacharias Moutoukias. Réseaux personnels et autorité coloniale : Les négociants de Buenos Aires au XVIIIe siècle. *Annales. Histoire, Sciences Sociales*, 47(4-5):889–915, October 1992. 35

[98] Andrej Mrvar and Vladimir Batagelj. Analysis and visualization of large networks with program package Pajek. *Complex Adaptive Systems Modeling*, 4(1), April 2016. 40, 71

[99] Natural earth. 72

[100] Neo4j graph data platform. 63, 64, 82

[101] Rolla Nicoletta. Mobilité et conflits. Travailler sur les chantiers de construction piémontais dans la première moitié du XVIIIe siècle. In Andrea Caracausi and Marco Schnyder, editors, *Travail et Mobilité En Europe (XVIe-XIXe Siècles)*, Coll. Histoire et Civilisations. Presses universitaires du Septentrion, Villeneuve d'Ascq, 2018. 54

[102] Carolina Nobre, Marc Streit, and Alexander Lex. Juniper: A Tree+Table Approach to Multivariate Graph Visualization. *IEEE Transactions on Visualization and Computer Graphics*, 25(1):544–554, January 2019. 39

[103] Gérard Noiriel. Naissance du métier d'historien. *Genèses. Sciences sociales et histoire*, 1(1):58–85, 1990.

[104] Maryjane Osa. *Solidarity And Contention: Networks Of Polish Opposition*. Univ Of Minnesota Press, Minneapolis, first edition edition, July 2003. 11, 49

[105] John F. Padgett and Christopher K. Ansell. Robust Action and the Rise of the Medici, 1400-1434. *American Journal of Sociology*, 98(6):1259–1319, May 1993. 11, 12, 16, 36

[106] Pajek — Analysis and visualization of very large networks. 15, 18, 93

[107] Terence J. Parr and Russell W. Quong. ANTLR: A predicated-LL (k) parser generator. *Software: Practice and Experience*, 25(7):789–810, 1995. 82

[108] Vanessa Peña-Araya, Tong Xue, Emmanuel Pietriga, Laurent Amsaleg, and Anastasia Bezerianos. HyperStorylines: Interactively untangling dynamic hypergraphs. *Information Visualization*, 21(1):38–62, January 2022. 55

[109] Cindarella Sarah Maria Petz. *On Combining Network Research and Computational Methods on Historical Research Questions and Its Implications for the Digital Humanities*. PhD thesis, Technische Universität München, 2022. 12, 36, 45

[110] James P. Philips and Nasseh Tabrizi. Historical Document Processing: Historical Document Processing: A Survey of Techniques, Tools, and Trends, September 2020. 122

[111] Robert Pienta, Fred Hohman, Alex Endert, Acar Tamersoy, Kevin Roundy, Chris Gates, Shamkant Navathe, and Duen Horng Chau. VIGOR: Interactive Visual Exploration of Graph Query Results. *IEEE Transactions on Visualization and Computer Graphics*, 24(1):215–225, January 2018. 65

[112] Alexis Pister, Nicole Dufournaud, Pascal Cristofoli, Christophe Prieur, and Jean-Daniel Fekete. From Historical Documents To Social Network Visualization: Potential Pitfalls and Network Modeling. In *7th Workshop on Visualization for the Digital Humanities (VIS4DH)*, 2022. 43

[113] Antoine Prost. *Douze Leçons sur l'histoire*. Média Diffusion, April 2014. 12, 13, 21, 26, 27

[114] R Core Team. *R: A Language and Environment for Statistical Computing*. R Foundation for Statistical Computing, Vienna, Austria, 2014. 64, 93

[115] Eric Ragan, Endert Alex, Jibonananda Sanyal, and Jian Chen. Characterizing Provenance in Visualization and Data Analysis: An Organizational Framework of Provenance Types and Purposes. *IEEE Transactions on Visualization and Computer Graphics*, 22(1), January 2016. 65

[116] Ramana Rao and Stuart K. Card. The table lens: Merging graphical and symbolic representations in an interactive focus + context visualization for tabular information. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, CHI '94, pages 318–322, New York, NY, USA, 1994. Association for Computing Machinery. 117

[117] Donghao Ren, Bongshin Lee, and Matthew Brehmer. Charticulator: Interactive Construction of Bespoke Chart Layouts. *IEEE Transactions on Visualization and Computer Graphics*, 25(1):789–799, January 2019. 65

[118] Pedro Ribeiro and Fernando Silva. Discovering Colored Network Motifs. In Pierluigi Contucci, Ronaldo Menezes, Andrea Omicini, and Julia Poncela-Casasnovas, editors, *Complex Networks V*, Studies in Computational Intelligence, pages 107–118, Cham, 2014. Springer International Publishing. 64

[119] Giulio Rossetti and Rémy Cazabet. Community discovery in dynamic networks: A survey. *ACM Comput. Surv.*, 51(2), February 2018. 97

[120] Fabrice Rossi, Nathalie Vialaneix, and Florent Hautefeuille. Exploration of a large database of French notarial acts with social network methods. *Digital Medievalist*, 9:2013, July 2014. 62

[121] Juan A. Rubio-Mondejar and Josean Garrues-Irurzun. Women entrepreneurs and family networks in Andalusia (Spain) during the second industrial revolution. *Business History*, pages 1–22, May 2022. 11

[122] C.J. Rueda and Catedral de Buenos Aires. *Matrimonios de La Catedral de Buenos Aires, 1747-1823*. Number v. 2 in Fuentes Históricas y Genealógicas Argentinas. Fuentes Históricas y Genealógicas Argentinas, 1989. 54

[123] Anni Sairio. Methodological and practical aspects of historical network analysis: A case study of the Bluestocking letters. In Arja Nurmi, Minna Nevala, and Minna Palander-Collin, editors, *Pragmatics & Beyond New Series*, volume 183, pages 107–135. John Benjamins Publishing Company, Amsterdam, 2009. 50

[124] Bahador Saket, Paolo Simonetto, and Stephen Kobourov. Group-level graph visualization taxonomy. In N. Elmqvist, M. Hlawitschka, and J. Kennedy, editors, *EuroVis - Short Papers*. The Eurographics Association, 2014. 98

[125] Arvind Satyanarayan, Dominik Moritz, Kanit Wongsuphasawat, and Jeffrey Heer. Vega-lite: A grammar of interactive graphics. *IEEE Trans. Vis. Comput. Graphics*, 23(1):341–350, 2016. 24, 82

[126] Shrutika S. Sawant and Manoharan Prabukumar. A review on graph-based semi-supervised learning methods for hyperspectral image classification. *The Egyptian Journal of Remote Sensing and Space Science*, 2018. 97

[127] John Scott. Social Network Analysis. *Sociology*, 22(1):109–127, February 1988. 21, 31, 33, 41, 49

[128] Vanessa Serrano Molinero, Benjamin Bach, Catherine Plaisant, Nicole Dufournaud, and Jean-Daniel Fekete. Understanding the use of the vistorian: Complementing logs with context mini-questionnaires. In *Visualization for the Digital Humanities Workshop*, Phoenix, United States, October 2017. 39, 40, 41, 48, 57

[129] Rachel Shadoan and Chris Weaver. Visual Analysis of Higher-Order Conjunctive Relationships in Multidimensional Data Using a Hypergraph Query System. *IEEE Transactions on Visualization and Computer Graphics*, 19(12):2070–2079, December 2013. 64

[130] Termeh Shafie, David Schoch, Jimmy Mans, Corinne Hofman, and Ulrik Brandes. Hypergraph Representations: A Study of Carib Attacks on Colonial Forces, 1509-1700. *Journal of Historical Network Research*, pages 52–70 Pages, October 2017. 62

[131] Ben Shneiderman. Dynamic queries for visual information seeking. *IEEE Softw.*, 11(6):70–77, November 1994. 75

[132] Georg Simmel. *Soziologie: Untersuchungen über die Formen der Vergesellschaftung*. Duncker & Humblot, Berlin, 7. aufl edition, 2013. 34

[133] Marc A. Smith, Ben Shneiderman, Natasa Milic-Frayling, Eduarda Mendes Rodrigues, Vladimir Barash, Cody Dunne, Tony Capone, Adam Perer, and Eric Gleave. Analyzing (social media) networks with NodeXL. In John M. Carroll, editor, *Proceedings of the Fourth International Conference on Communities and Technologies, C&T 2009, University Park, PA, USA, June 25-27, 2009*, pages 255–264. ACM, 2009. 15, 40, 62, 71

[134] SNA — Tools for social network analysis.

[135] John Snow. On the Mode of Communication of Cholera. *Edinb Med J*, 1(7):668–670, January 1856. 22

[136] John T. Stasko, Carsten Görg, and Zhicheng Liu. Jigsaw: Supporting investigative analysis through interactive visualization. *Inf. Vis.*, 7(2):118–132, 2008. 41, 53, 57, 121

[137] Alexander Strehl and Joydeep Ghosh. Cluster ensembles—a knowledge reuse framework for combining multiple partitions. *Journal of machine learning research*, 3(Dec):583–617, 2002. 99

[138] Shazia Tabassum, Fabiola S. F. Pereira, Sofia Fernandes, and João Gama. Social network analysis: An overview. *WIREs Data Mining and Knowledge Discovery*, 8(5):e1256, 2018. 11, 15, 33

[139] Natkamon Tovanich, Alexis Pister, Gaelle Richer, Paola Valdivia, Christophe Prieur, Jean-Daniel Fekete, and Petra Isenberg. VAST 2020 Contest Challenge: GraphMatchMaker: Visual Analytics for Graph Comparison and Matching. *IEEE Computer Graphics and Applications*, pages 1–1, 2021. 64, 65

[140] John W. Tukey. The Future of Data Analysis. *The Annals of Mathematical Statistics*, 33(1):1–67, 1962. 22

[141] John W. Tukey. *Exploratory Data Analysis*. Pearson, Reading, Mass, 1er édition edition, January 1977. 15, 25

[142] Paola Valdivia, Paolo Buono, Catherine Plaisant, Nicole Dufournaud, and Jean-Daniel Fekete. Analyzing Dynamic Hypergraphs with Parallel Aggregated Ordered Hypergraph Visualization. *IEEE Trans. Visual. Comput. Graphics*, 27(1):1–13, January 2021. 39, 55, 91, 122

[143] Guido van Rossum. Python tutorial. Technical Report CS-R9526, Centrum voor Wiskunde en Informatica (CWI), Amsterdam, May 1995. 64

[144] Ingeborg van Vugt. Using multi-layered networks to disclose books in the republic of letters. *Journal of Historical Network Research*, 1(1):25–51, October 2017. 51

[145] Corinna Vehlow, Fabian Beck, and Daniel Weiskopf. The state of the art in visualizing group structures in graphs. In R. Borgo, F. Ganovelli, and I. Viola, editors, *Eurographics Conference on Visualization (EuroVis) - STARs*. The Eurographics Association, 2015. 98

[146] VisMaster: Visual analytics — Mastering the information age. 113

[147] Kiri Wagstaff, Claire Cardie, Seth Rogers, Stefan Schrödl, et al. Constrained k-means clustering with background knowledge. In *Icml*, volume 1, pages 577–584, 2001. 97

[148] Stanley Wasserman and Katherine Faust. *Social Network Analysis: Methods and Applications*. Cambridge University Press, November 1994. 15, 33, 41

[149] Charles Wetherell. Historical Social Network Analysis. *Int Rev of Soc His*, 43(S6):125–144, December 1998. 11, 13, 21, 35, 43, 49, 50, 61

[150] Kai Xu, Alvitta Ottley, Conny Walchshofer, Marc Streit, Remco Chang, and John Wenskovitch. Survey on the Analysis of User Interactions and Visualization Provenance. *Computer Graphics Forum*, 39(3):757–783, June 2020. 65

[151] Michelle X. Zhou. "Big picture": Mixed-initiative visual analytics of big data. In *Proceedings of the 6th International Symposium on Visual Information Communication and Interaction*, VINCI '13, page 120, New York, NY, USA, 2013. Association for Computing Machinery. 98