

===== This thesis aims at identifying theoretically and with concrete propositions how visual analytics can support historians in their social network analysis process. Historical social network analysis is a method to study social relationships between groups of actors (families, institutions, companies, etc.) through a reconstruction of relationships of the past from historical documents, such as marriage acts, migration forms, birth certificates, and censuses. The use of visualization and analytical methods lets social historians explore and describe the social structure shaping those groups while explaining sociological phenomena and individual behaviors through computed network measures. However, the inspection and encoding of the sources leading to a finalized network is intricate and often results in inconsistencies, errors, distortions, and traceability problems, and current visualization tools typically have usability and interpretability issues. For these reasons, social historians are not always able to make thorough historical conclusions: many studies consist of qualitative descriptions of network drawings highlighting the presence of motifs such as cliques, components, bridges, etc. The goal of this thesis is therefore to propose visual analytics tools integrated into the whole social historians' workflow with guided and easy-to-use analysis capabilities. Towards this goal, I formalize the workflow of historical network analysis from collaborations with social historians, starting at the acquisition of sources to the final visual analysis. By highlighting recurring pitfalls, I point out that tools supporting this process should satisfy traceability, simplicity, and document reality principles to ease back and forth between the different steps, provide tools easy to manipulate, and not distort the content of sources with modifications and simplifications. The network modeling influences deeply those properties given the high diversity in properties of network models. I propose to model historical sources into bipartite multivariate dynamic social networks with roles as they provide a good trade-off of simplicity and expressiveness while modeling explicitly the documents, hence letting users encode, correct, and analyze their data with the same abstraction and tools. I propose two interactive visual interfaces to manipulate, explore, and analyze this data model, with a focus on usability and interpretability. The first system ComBiNet 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 and comparing them, social historians are able to find inconsistencies in their annotations and answer high-level 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 interactive exploration of the network. Both systems have been¹designed with continuous feedback from social historians, and aim to increase the traceability, simplicity, and document reality of visual analytics supported historical social network research. 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. Systems with a focus on those properties—traceability, simplicity, and document reality—can limit the introduction of bias while lowering the requirements for the use of quantitative methods for historians and social scientists which has always

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: Cette thèse vise à identifier théoriquement et concrètement comment l'analyse visuelle peut aider les historiens dans leur processus d'analyse de réseaux sociaux. L'analyse de réseaux sociaux est une méthode utilisée en histoire sociale qui vise à étudier les relations sociales au sein de groupes d'acteurs (familles, institutions, entreprises, etc.) en reconstruisant les relations du passé à partir de documents historiques, tels que des actes de mariages, des actes de naissances, ou des recensements. L'utilisation de méthodes visuelles et analytiques leur permet d'explorer la structure sociale formant ces groupes et de relier des mesures structurelles à des hypothèses sociologiques et des comportements individuels. Cependant, l'inspection, l'encodage et la modélisation des sources menant à un réseau finalisé donnent souvent lieu à des erreurs, des distorsions et des problèmes de traçabilité, et les systèmes de visualisation actuels présentent souvent des défauts d'utilisabilité et d'interprétabilité. En conséquence, les historiens ne sont pas toujours en mesure de faire des conclusions approfondies à partir de ces systèmes : beaucoup d'études se limitent à une description qualitative d'images de réseaux, surlignant la présence de motifs d'intérêts (cliques, îlots, ponts, etc.). Le but de cette thèse est donc de proposer des outils d'analyse visuelle adaptés aux historiens afin de leur permettre une meilleure intégration de leur processus global et des capacités d'analyse guidées. En collaboration avec des historiens, je formalise le processus d'une analyse de réseau historique, de l'acquisition des sources jusqu'à l'analyse finale, en posant comme critère que les outils utilisés dans ce processus devraient satisfaire des principes de traçabilité, de simplicité et de réalité documentaire (i.e., que les données présentées doivent être conformes aux sources) pour faciliter les va-et-vient entre les différentes étapes et la prise en main par l'utilisateur et ne

pas distordre le contenu des sources. Pour satisfaire ces propriétés, je propose de modéliser les sources historiques en réseaux sociaux bipartis multivariés dynamiques avec rôles. Ce modèle intègre explicitement les documents historiques sous forme de nœuds, ce qui permet aux utilisateurs d'encoder, de corriger et d'analyser leurs données avec les mêmes outils. Je propose ensuite deux interfaces d'analyse visuelle permettant, avec une bonne utilisabilité et interprétabilité, de manipuler, d'explorer et d'analyser ce modèle de données. Le premier système ComBiNet offre une exploration visuelle de l'ensemble des dimensions du réseau à l'aide de vues coordonnées et d'un système de requêtes visuelles permettant d'isoler des individus ou des groupes et de comparer leurs structures topologiques et leurs propriétés. L'outil permet également de détecter les motifs inhabituels et ainsi de déceler les éventuelles erreurs dans les annotations. Le second système, PK-Clustering, est une proposition d'amélioration de l'utilisabilité et de l'efficacité des mécanismes de clustering dans les systèmes de visualisation de réseaux sociaux. L'interface permet de créer des regroupements pertinents à partir des connaissances a priori de l'utilisateur, du consensus algorithmique et de l'exploration du réseau dans un cadre d'initiative mixte. Les deux systèmes ont été conçus à partir des besoins et retours continus d'historiens, et visent à augmenter la traçabilité, la simplicité, et la réalité documentaire des sources dans le processus d'analyse de réseaux historiques. « « « < HEAD Je conclus sur la nécessité d'une meilleure intégration des systèmes d'analyse visuelle dans le processus de recherche des historiens. Cette intégration nécessite des outils plaçant les utilisateurs au centre du processus avec un accent sur la flexibilité et l'utilisabilité, limitant ainsi l'introduction de biais et les barrières d'utilisation des méthodes quantitatives, qui subsistent en histoire.

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

Keywords: visual analytics, social network analysis, social network visualization, social history, historical networks

Abstract: «««< HEAD This thesis aims at identifying theoretically and concretely how visual analytics can support historians in their social network analysis process. Historical social network analysis is a method to study social relationships between groups of actors (families, institutions, companies, etc.) through a reconstruction of relationships of the past from historical documents, such as marriage acts, migration forms, birth certificates, and censuses. The use of visualization and analytical methods lets social historians explore and describe the social structure shaping those groups while explaining sociological phenomena and individual behaviours through computed network measures. However, the inspection and encoding of the sources leading to a finalized network is intricate and often results in inconsistencies, errors, distortions, and traceability problems, and current visualization tools typically have usability and interpretability issues. For these reasons, social historians are not always able to make thorough historical conclusions: many studies consist in qualitative description of network drawings highlighting the presence of motifs such as cliques, components, bridges, etc. The goal of this thesis is therefore to propose visual analytics tools integrated in the global social historians workflow, with guided and easy-to-use analysis capabilities. From collaborations with historians, I formalize the workflow of historical network analysis starting at the acquisition of sources to the final visual analysis. By highlighting recurring pitfalls, I point out that tools supporting this process should satisfy traceability, simplicity, and document reality principles to ease back and forth between the different steps, provide tools easy to manipulate, and not distort the content of sources with modifications and simplifications. To satisfy those properties, I propose to model historical sources into bipartite multivariate

dynamic social networks with roles as they provide a good tradeoff of simplicity and expressiveness while modeling explicitly the documents, hence letting users encode, correct, and analyze their data with the same abstraction and tools. I then propose two interactive visual interfaces to manipulate, explore, and analyze this data model, with a focus on usability and interpretability. The first system ComBiNet allows an interactive exploration leveraging the structure, time, localization, and attributes of the data model with the help of coordinated views and a visual query system allowing users to isolate interesting groups and individuals, and comparing their position, structures, and properties. It also lets them highlight erroneous and inconsistent annotations directly in the interface. The second system, PK-Clustering, is a concrete proposition to enhance 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 interactive 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 visual analytics supported historical social network research. I conclude with discussions on the potential merging of both tools, and more globally on research directions towards a better integration of visual analytics systems on the whole workflow of social historians. Systems with a focus on those properties—traceability, simplicity, and document reality—can limit the introduction of bias while lowering the requirements for the use of quantitative methods for historians and social scientists which has always been a controversial discussion among practitioners.

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On the usage of footnotes

This thesis led me to read many history work, in which footnotes are more than widespread. I grew rather fond of them and explain why you will see several of them across this manuscript.

On the usage of the pronouns we and I

Most of the research described in this thesis was highly collaborative. I would like to thank deeply all my collaborators for their help, support, and thoughtful discussions. In the writing, I hence use “we” for collaborative parts and “I” for the parts I have mostly done myself.

Contents

1	Introduction	1
1.1	Social History and Historical Social Network Analysis	2
1.2	Visualization and Visual Analytics	4
1.3	Visual Analytics Supported Historical Network Research	5
1.4	Contributions and Research Statement	9
2	Related Work	11
2.1	Visualization	12
2.1.1	Information Visualization	12
2.1.2	Visual Analytics	15
2.2	Quantitative Social History	16
2.2.1	History, Social History, and Methodology	16
2.2.2	Quantitative History	18
2.2.3	Digital Humanities	19
2.3	Historical Social Network Analysis	20
2.3.1	Sociometry to SNA	21
2.3.2	Methods and Measures	23
2.3.3	Historical Social Network Analysis	25
2.3.4	Network Modeling	25
2.4	Social Network Visualization	27
2.4.1	Graph Drawing	28
2.4.2	Social Network Visual Analytics	29
3	Historical Social Network Analysis Process, Pitfalls, and Network Modeling	33
3.1	Context	34
3.2	Related Work	35
3.2.1	History Methodology	35
3.2.2	Historian Workflows	36
3.3	Historical Social Network Analysis Workflow	37
3.3.1	Examples	37
3.3.2	Workflow	38
3.3.3	Visual Analytics Supported Historical Social Network Analysis	40
3.4	Network Modeling and Analysis	42
3.4.1	Network Models	43
3.4.2	Bipartite Multivariate Dynamic Social Network	46
3.5	Applications	47
3.6	Discussion	48
3.7	Conclusion	48

4	ComBiNet: Visual Query and Comparison of Bipartite Dynamic Multivariate Networks with Roles	51
4.1	Context	52
4.2	Related Work	54
4.2.1	Graphlet Analysis	54
4.2.2	Visual Graph Querying	55
4.2.3	Visual Graph Comparison	55
4.2.4	Provenance	56
4.3	Task Analysis and Design Process	56
4.3.1	Scenarios	56
4.3.2	Tasks Analysis	58
4.4	ComBiNet System	59
4.4.1	Visualizations	59
4.4.2	Query Panel	63
4.4.3	Comparison	69
4.4.4	Implementation	71
4.5	Use Cases	72
4.5.1	Construction Sites in Piedmont (#1)	72
4.5.2	French Genealogy (#2)	74
4.5.3	Marriage Acts in Buenos Aires (#3)	76
4.5.4	Sociology Theses in France	77
4.6	Formative Usability Study	79
4.6.1	Feedback	80
4.7	Discussion	80
4.8	Conclusion and Future Work	81
5	PK-Clustering: Integrating Prior Knowledge in Mixed-Initiative Social Network Clustering	83
5.1	Context	84
5.2	Related Work	87
5.2.1	Graph Clustering	87
5.2.2	Semi-supervised Clustering	87
5.2.3	Mixed-Initiative Systems and Interactive Clustering	88
5.2.4	Groups in Network Visualization	88
5.2.5	Ensemble Clustering	88
5.2.6	Summary	89
5.3	PK-clustering	89
5.3.1	Overview	89
5.3.2	Specification of Prior Knowledge	91
5.3.3	Running the Clustering Algorithms	91
5.3.4	Matching Clustering Results and Prior Knowledge	92
5.3.5	Ranking the Algorithms	93
5.3.6	Reviewing the Ranked List of Algorithms	94

5.3.7	Reviewing and Consolidating Final Results	95
5.3.8	Wrapping up and Reporting Results	99
5.4	Case Studies	100
5.4.1	Marie Boucher Social Network	100
5.4.2	Lineages at VAST	102
5.4.3	Feedback from Practitioners	104
5.5	Discussion	105
5.5.1	Limitations	106
5.5.2	Performance	106
5.6	Conclusion	107
6	Conclusion	109
6.1	Summary	109
6.2	Discussion	110
6.3	Perspectives	113
6.4	Conclusion	116

List of Figures

1.1	Business contract originated from Nantes (France) during the 17th century. See [66] for more detail of the historian process to analyze her sources.	4
1.2	Marriage, partnership, trading, banking, and real estate networks of the powerful families of Florence from [171]. We can see the central position in the network of the Medici Family.	6
1.3	Abstraction of the VA process. It is characterized by continuous interactions between the data, visualizations, models, and knowledge. Image from [120]. . .	7
1.4	Node-link diagram of a medieval social network of peasants, produced with a force-directed layout, commonly used in SNA softwares. The picture is note very informative and only reveal a semblance of community structure. Image from [32].	8
2.1	Categorization of visual variables which can be used to represent network data, resulting in many different network representations. Image from [24].	13
2.2	Anscombe quartet. The four datasets have the same descriptive statistics (average, variance, correlation coefficient) but very different structures. Image from [8].	14
2.3	TULIP software is designed for application-independent network visual analytics [11]. The view shows a dataset among multiple interactive coordinated views. Users can also apply data mining algorithms on the data to extract interesting patterns.	16
2.4	Correspondence letters of Benjamin Franklin and his close relationships, visualized with a map and a histogram, accessible online on the republic of letter website [70].	20
2.5	Moreno's original sociogram of a class of first grades from [160] (left). The diagram shows 21 boys (triangles) and 14 girls (circles). The same sociogram using modern practices generated from Gephi from [92] (right). The color encodes the number of incoming connections.	22
2.6	All possible graphlets of size 2 to 5 for undirected graphs	23
2.7	Cicero's personal communication network represented with a node-link diagram. Image from [4]	26
2.8	Different criteria are proposed to enhance node-link diagram readability. Image from [127]	28
2.9	NodeTrix system showing a scientific collaboration social network with clusters. Each cluster is represented as a matrix, Image from [108].	29
2.10	Vistorian interface [201] used to explore a historical social network of business trades in the 17th century, with a coordinated node-link diagram and a matrice view.	30

3.1	HSNA workflow is split into five steps: textual sources acquisition, digitization, annotation, network creation, and network visualization/analysis. Practitioners typically have to do back and forth during the process. I list potential pitfalls for each step.	38
3.2	Three properties essential to VA systems supporting the social historians workflow: <i>traceability</i> , <i>document reality</i> , and <i>simplicity</i>	41
3.3	bipartite multivariate dynamic network modeling for two cases of marriage acts of example #3. Some marriage acts mention the parents of the spouses, which is a relationship different than the marriage in itself. This case can be modeled using a document model (a) or an event model (c) by splitting the document into several different event nodes. The other case refers to documents that do not mention the parents (b), and in that case, the network represents both the documents and the events with the same model. M: Marriage, H: Husband, W: Wife, T: Witness, (H/W)(M/F): Husband/Wife Mother/Father. Yellow links refer to parenting mentions/relationships.	49
4.1	The ComBiNet system was used to compare two subgroups of a social network of contracts from [54], extracted with dynamic visual queries. (A) and (B) show the two visual queries created by the user in the query panel using an interactive node-link diagram editor (V6), dynamic query widgets (V7), and the equivalent Cypher script (V8). The right part shows ComBiNet's global interface in <i>comparison</i> mode: (V1) Network visualization panel, (V2) Map of the geolocalized nodes, (V3) Table of persons, (V4) Graph measures comparison, (V5) Attribute distribution plots, and (V9) Provenance tree. The two visual queries on the left, translated into Cypher queries below, select the "Menafooglio" family on the left, and the "Zo" family on the right, along with their construction contracts and close collaborators.	61
4.2	ComBiNet interface wreal-timeith the dataset of collaboration #1. The user selected the <code>__year</code> attribute, showing the distribution of document years with a histogram (bottom right), and coloring the documents node on the bipartite view (left) and map view simultaneously (right).	63
4.3	All link creation possibilities: Any link type (left), one selected link type, here guarantor (middle left), the union of several link types (middle right), several links with different types (right)	64
4.4	Visual queries created to answer questions 2 and 6 of our collaboration #1. (a) The visual query retrieves individuals who are mutually guarantors to each other in separate construction contracts. (b) The two visual queries retrieve the documents—along with the signatories—of Torino (<i>Turin</i> in french) (left) and of Torino's surroundings (<i>Turin Territoire</i> and <i>Piemont</i>) (right).	65
4.5	Widget designs for the different attribute types: checkboxes for categorical attributes (top), text input for nominal attributes (middle), and a double slider for numerical attributes (bottom). The categorical attribute example shows the inputs letting users create new constraints for other attributes and other nodes.	66

4.6	Results of question 2 of collaboration #1: (a) shows a subset of the table view with every occurrence of the pattern found. (b) shows the summary panel, with the graph measures and the attributes view with the <i>origin</i> attribute selected and the Sankey option checked. It allows us to see the attribute distribution of the persons included in the pattern and see if there is a relationship between persons who are mutually guarantors and their origin.	68
4.7	Two ways of showing the distribution of “type chantier” (type of works), a categorical attribute with three possible values “ <i>religious</i> ”, “ <i>military</i> ”, and “ <i>civilian</i> ”. (a) A query matching the contracts made by the same person (<i>per1</i>) as an “approbator” (green link to <i>doc2</i>) after being a “guarantor” (blue link to <i>doc1</i>) using the constraint (<i>doc2._year</i> > <i>doc1._year</i>). (b) Stacked bar chart for the matches, the earlier contract (<i>doc1</i>), the older contract (<i>doc2</i>), and (c) Sankey diagram with the early values on the left and the last on the right. The Sankey diagram reveals the value changes between the two documents: the guarantor who worked initially on religious work switched to military work. . . .	69
4.8	Provenance tree to answer question 2 of collaboration #1: left branch leads to Torino documents (the node is labeled as A) while right branch leads to surrounding documents (the node is labeled as B). The user hovers over one node, revealing a tooltip that shows the visualization of the node’s query. . . .	70
4.9	Comparison table of the network measures for Torino subgraph (A) and Torino’s surroundings subgraph (B).	71
4.10	Distribution of the type of constructions, the years, and the betweenness centrality for the documents and signatories of Torino (A), Torino’s surroundings (B), and the whole graph (top).	72
4.11	Menafoglio (a) and Zo (b) families were retrieved with queries and highlighted in the bipartite node-link and map views.	73
4.12	Attributes distributions plots between the whole graph, the <i>Menafoglio</i> family (A), the <i>Zo</i> family (B), and $A \cap B$, for the <i>region</i> , <i>type_chantier</i> , <i>material type</i>	74
4.13	Map of the migrations in France which occurred across several generations. . .	75
4.14	Migrations across departments over three generations	76
4.15	Sankey diagrams showing the migration of people in the 18th (left) and 19th (right) centuries, extracted from their birth and death places.	76
4.16	ComBiNet used to request persons appearing as husband, wife, or witness in two marriages that occurred 70 years apart or more.	77
4.17	ComBiNet used for exploring theses of sociology defended in France between 2016 and 2021. The bipartite and map views show an overview of two visions of the network. The user selects the <i>region</i> attribute, showing the geographical distribution of the defended thesis.	78

4.18	Sociology thesis dataset explored with ComBiNet. The user constructed a visual query to see if there are symmetrical relationships between thesis directors and reviewers (or jury directors). The <i>region</i> attribute is selected with the Sankey option, letting the user see if there are correlations between the regions of the thesis found in this pattern.	79
5.1	Process of traditional clustering (left) and our PK-Clustering approach (middle and right). The output of traditional clustering is a possible clustering, using an algorithm among many choices. The output of PK-Clustering is a clustering supported by algorithms' consensus and validated (fully or partially) according to the user's PK.	86
5.2	Prior Knowledge specification, the user defined two groups composed of two members.	91
5.3	Red edges represent the prior knowledge matching	93
5.4	Two different modalities for the ranked list of algorithms. Top: persons are shown as circles. Bottom: aggregated view. Colors indicate the matching group. Gray indicates no match. White indicates extra nodes or clusters.	95
5.5	Reviewing and comparing results of multiple algorithms. One algorithm is selected to order the names and group them, but icons show how other algorithms cluster the nodes differently, summarized in the consensus bar on the left.	97
5.6	The user quickly drags on consecutive icons (in yellow) representing the suggestions made by one algorithm to validate node clustering. Once the cursor is released the validated nodes appear as squares icons in the Consolidated Knowledge column.	97
5.7	Suggestion of extra clusters. The two PK-groups (red and blue) are validated (nodes in the consensus column are all squared). One extra clusters is proposed by the Louvain algorithm, labeled as 2. Hovering over the cluster 2, the consensus is displayed by the green diamonds. This feedback is also visible in the graph.	99
5.8	The dataset has been fully consolidated. The persons are grouped and colored by the consolidated knowledge. The user decided to assign Claude, Guillaume, Madeleine and Renexent to cluster <i>C</i> , by taking into account the graph and the consensus of the algorithms.	100
5.9	Two main phases of PK-clustering. On the left, the user has specified the Prior Knowledge (PK) groups (top left) and then reviews the list of algorithms ranked according to how well they match the PK. On the right, the user compared the detailed results of selected algorithms and consolidated the results. From the initial specification of three groups and three people, 4 relevant clusters were obtained with 37 people in total, plus one unclassified node (<i>Others</i> group).	101
5.10	Summary report of the consolidated knowledge for the Marie Boucher case study.	102
5.11	Computing the Lineages of VAST authors: Prior Knowledge from Alice and results of the clusterings matching it.	103

5.12	Four consolidated groups in the VAST dataset: C North, RVAC, Andrienko and London	104
6.1	Potential place of VA in the HSNA workflow defined in chapter 3.	109
6.2	Prototype of a document-centered dynamic layout for bipartite multivariate dynamic networks, visualized with data of construction contracts in Piedmont (see collaboration #1 in chapter 3). The layout can show the mention of persons encoded with their roles (top) or the documents and their properties (bottom). Here, the <i>region</i> attribute is selected, hence coloring construction contract depending on their location.	115

List of Tables

2.1	Comparison table of most widely used visualization and analytical tool for SNA. Visualizations: number of different visualization techniques, and layouts. SNA Measures and Models: number of proposed SNA measures and algorithms. Clustering: Number of proposed clustering algorithms. Filtering: Possibilities of filtering according to various criteria. Interaction/Direct Manipulation: Number of possible interaction mechanisms directly applicable to the visualizations. . . .	30
3.1	Resulting networks using different models produced by one document of the examples detailed in §3.3.1: co-occurrence, unipartite and bipartite models. The first column shows the partial transcription of real documents (simplification for collaboration #1). Colors represent annotations concerning the persons mentioned, their roles, and their attributes. Underlines refer to information related to the events and which can be encoded as document/event attributes. Only time is represented for simplification, but other attributes would follow the same schema. H: Husband, W: wife, T: Witness, M: Marriage, A_N : Associate, G: Guarantor, Ap: Approbator, C: Construction, F: Father, M: Mother, C: Child.	45
4.1	Tasks to support during exploration, according to our expert collaborators, are split into 3 main high-level tasks.	60
4.2	Comparison of the data model of several VA systems aimed at exploring bipartite social networks.	60

Publications

Publications related to the thesis

- A. Pister, P. Buono, J.-D. Fekete, C. Plaisant, and P. Valdivia, Integrating Prior Knowledge in Mixed-Initiative Social Network Clustering, *IEEE Transactions on Visualization and Computer Graphics*, vol. 27, no. 2, pp. 1775–1785, Feb. 2021, doi:[10.1109/TVCG.2020.3030347](https://doi.org/10.1109/TVCG.2020.3030347).
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- A. Pister, N. Dufournaud, P. Cristofoli, C. Prieur, J.-D. Fekete, From Historical Documents To Social Network Visualization: Potential Pitfalls and Network Modeling. *VIS4DH 2022 - 7th Workshop on Visualization for the Digital Humanities*, Oct 2022, Oklahoma City, United States.
- A. Pister, C. Prieur, and J.-D. Fekete. Visual Queries on Bipartite Multivariate Dynamic Social Networks. Poster, *EuroVis 2022 - 24th EG Conference on Visualization*, Jun 2022, Rome, Italy. doi:[10.2312/evp.20221115](https://doi.org/10.2312/evp.20221115)

Other Publications

- N. Tovanich, A. Pister, G. Richer, P. Valdivia, C. Prieur, J.-D. Fekete, and P. Isenberg. VAST 2020 Contest Challenge: GraphMatchMaker: Visual Analytics for Graph Comparison and Matching. *IEEE Computer Graphics and Applications*, IEEE, 2021, 42 (4), pp.89 - 102. doi:[10.1109/mcg.2021.3091955](https://doi.org/10.1109/mcg.2021.3091955).
- S. Di Bartolomeo, A. Pister, P. Buono, C. Plaisant, C. Dunne, and J.-D. Fekete. Six Methods for Transforming Layered Hypergraphs to Apply Layered Graph Layout Algorithms. *Computer Graphics Forum*, Wiley, 2022, *EuroVis 2022 - Conference Proceedings*, 41 (3), pp.1467-8659. doi:[10.1111/cgf.14538](https://doi.org/10.1111/cgf.14538).

1 Introduction

“My claim rests on the assumption that [...] researchers can learn the truth about social processes. At a minimum, they can distinguish between totally inadequate and less inadequate representations of social processes, thus opening the way to increasingly reliable knowledge.”

-Charles Tilly, [221]

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, traceability, and usability. *Historical Social Network Analysis (HSNA)* is a method—sometimes referred as a paradigm [235]—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 [82, 216] and constitute a powerful metaphor, especially in our time when many of our digital connections and interactions use an explicit network structure¹. This approach has first been formalized in sociology under the term *Social Network Analysis (SNA)* [82] and is now widely used in anthropology [156], geography [], and history [122]. Historians leverage historical documents—which are at the core of their profession [133]—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 [122, 233]. This approach has been followed successfully to study various subjects such as kinship [100], entrepreneurship [192], maritime routes [134], political power [171], political oppositions [170], and persecution [153]. 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 [97, 119, 139, 142], 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 [52, 65], 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 typically use

¹This analogy goes to the point that the term “social network” can refer both to the sociological metaphor for social relationships and to the social media platforms such as Facebook.

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 results [5]. 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 [171] or Gribaudo and Blum work on the social and professional shift during the 19th century in France [95].

The usage of visualization to graphically display networks is common in SNA² 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 [53]. Images of networks also constitute an efficient mean of communication, especially in scientific productions [81]. Many visualization techniques and softwares have thus been developed since the beginnings 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 typically enforce simple network models without proposing exploration mechanisms, beyond allowing to look at the network structure and computed measures. As a 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 [140]. *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 levels 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 [122, 175], 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 [26, 181]. 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, such as sovereigns [181]. 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 [220]. Later on in the 1960s, with the development of computer science, historians

²Historians and sociologists following network analyses typically use similar techniques and tools for analyzing their data. The differences 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.

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 [107] and economics [91]. 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 [40]. 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 [82]. This shift in the object of study from traditional social classes and aggregates to the observation of relationships of individuals remind the microhistory movement [87] 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 [233]. 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, and 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 exploratory process, where historians start to generate sociological hypotheses from the continuous extraction of insight and revelations of this process, similarly to grounded theory [89]. 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.” [140] 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

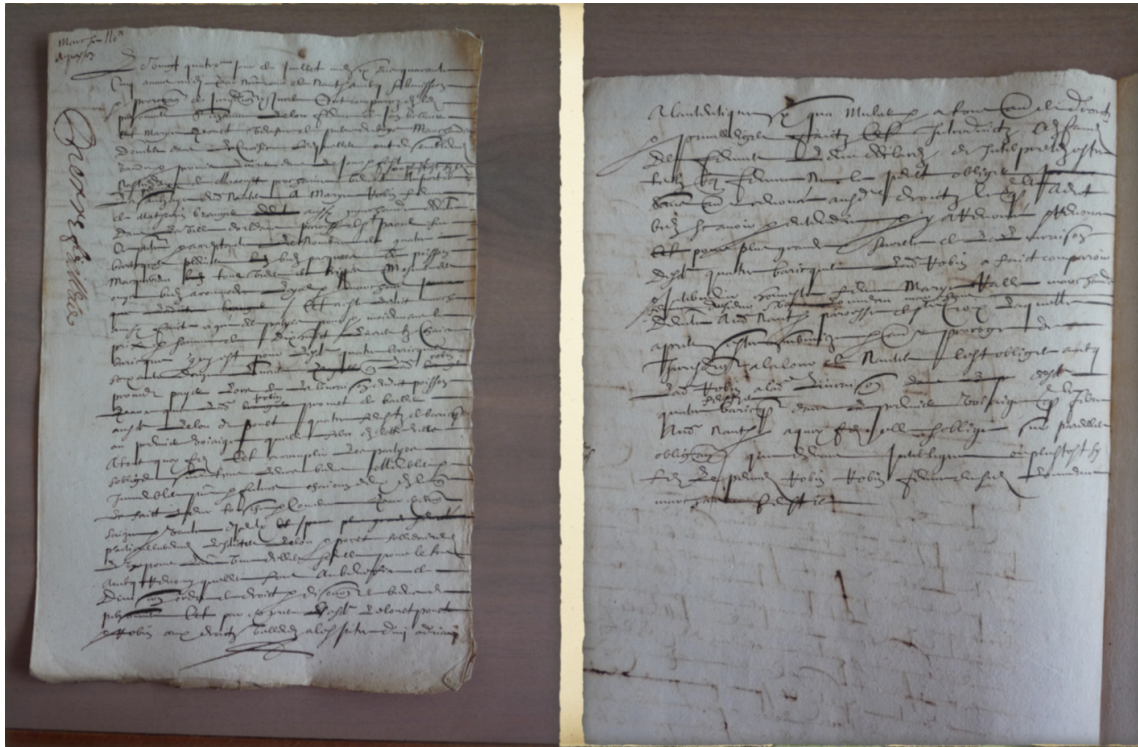


Figure 1.1 – Business contract originated from Nantes (France) during the 17th century. See [66] for more detail of the historian process to analyze her sources.

of Intelligence Analysis [61]. 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 [81, 237]—as it the case for many scientific fields³. Social scientists now widely 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 [43]. 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.

³the 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 [56].

Visualization has traditionally been used for confirmatory and communication purposes, particularly in empirical sciences [207]. 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 [224], 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” [81]. Social scientists very often represent their data using node-link diagrams, that we find in every production of reference in the field [35, 136, 216, 232].

Figure 1.2 shows a node-link representation of the network constructed by Padgett and Ansell 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 [17], Pajek [164], NodeXL [210], or Ucinet [117] 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 [120].

Figure 1.3 illustrates 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 [118].

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 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 [5]. VA should therefore support social historians in the entirety of their process, with a focus on usability and simplicity.

Currently, social historians spend a long time in their data acquisition, processing, encoding,

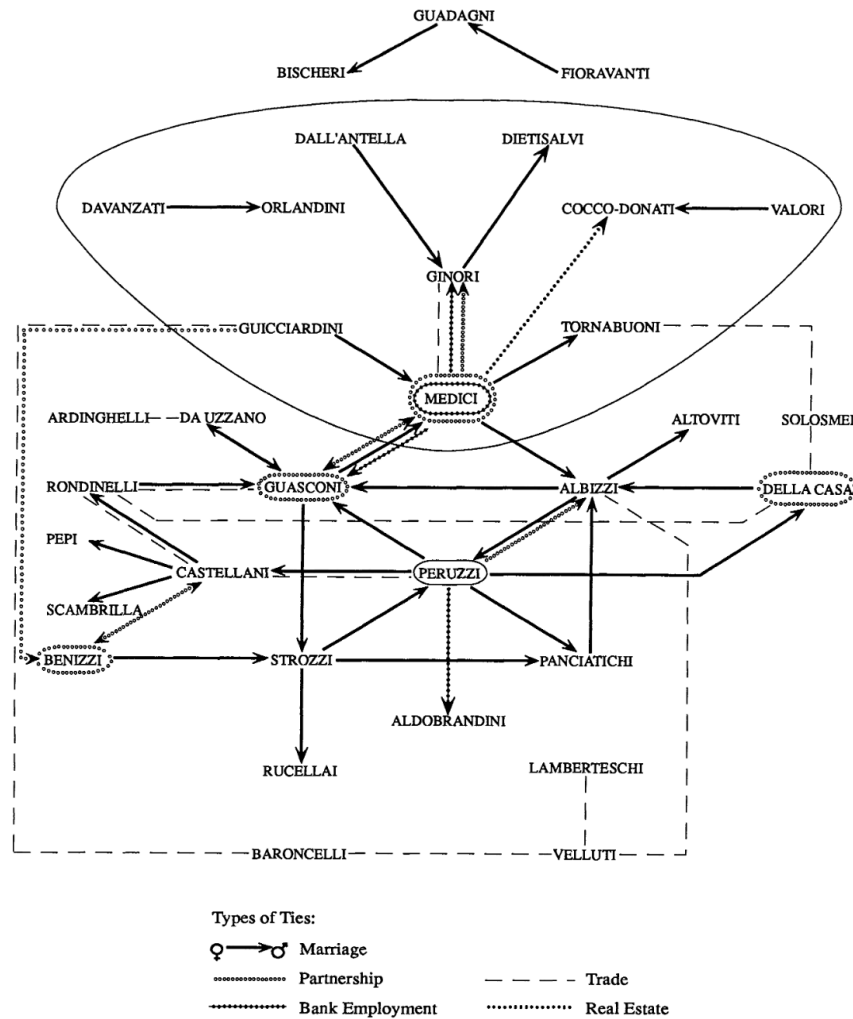


Figure 1.2 – Marriage, partnership, trading, banking, and real estate networks of the powerful families of Florence from [171]. We can see the central position in the network of the Medici Family.

and modeling steps which lead them to the construction of a network [66, 141]. 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 [139]. 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 [5, 140]. 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 [5, 63].

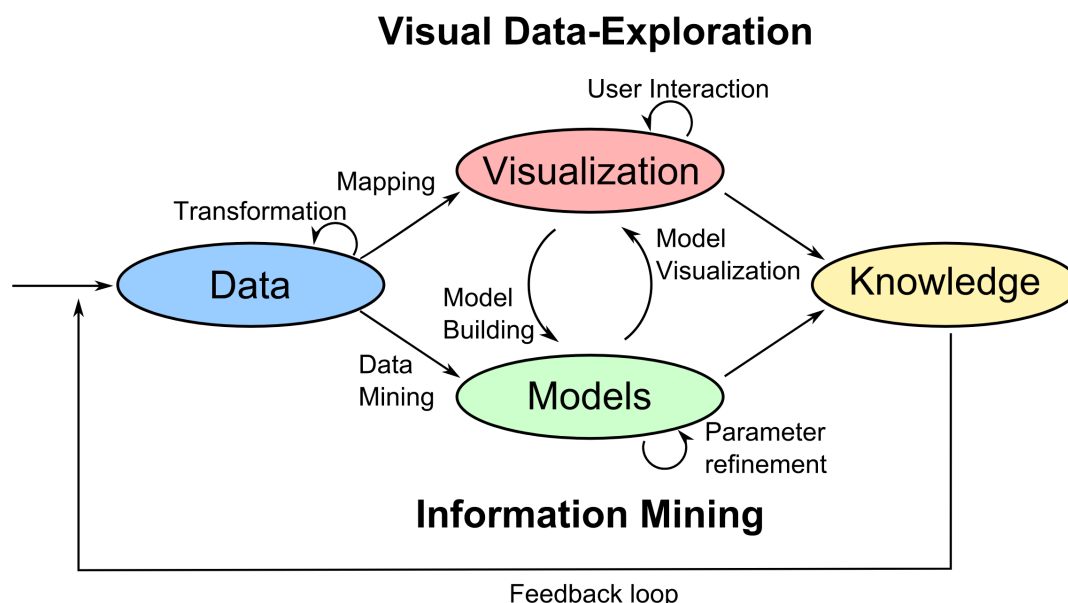


Figure 1.3 – Abstraction of the VA process. It is characterized by continuous interactions between the data, visualizations, models, and knowledge. Image from [120].

Practitioners also have to decide on a network model [52] (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 [139] and too complicated models are hard to manipulate [169]. 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. Proposing how to design such interfaces with proof-of-concepts is one of the goals of this thesis.

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” [188]. Such studies typically show one—or a couple—node-link diagram(s) which they describe with qualitative terms [140] 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” [48, 140] 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 does 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.



Figure 1.4 – Node-link diagram of a medieval social network of peasants, produced with a force-directed layout, commonly used in SNA softwares. The picture is not very informative and only reveals a semblance of community structure. Image from [32].

The lack of use of network analytical methods—which are numerous in modern SNA softwares⁴—have been in part explained by “math anxiety” [173]: it takes long effort to learn the mathematical concepts behind network measures and algorithms, and their relationships to sociological concepts [188], especially for practitioners without formal computer science and mathematical training. My claim is that current HSNA tools do not support social scientists

⁴See for example the long technical manuals of Pajek [164] and Ucinet [?]

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 [178]. 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 in their use of network methods, first by providing guidance and continuous feedback on the inspection, encoding, modification, and modeling process from the sources, and by providing complex exploration and analysis mechanisms supported by data mining capabilities. For this, such interfaces should 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 should satisfy *simplicity*, *document reality*, and *traceability* principles. I discuss and explain those principles 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 a high impact on 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 [5]. 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 [72]. 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, while satisfying *traceability*, *document reality*, and *simplicity* properties:

- Q1:** How to model historical documents into analyzable networks 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 addressing **Q3**.

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