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Analyse Visuelle pour l'Analyse de Réseaux Sociaux Historiques

Visual Analytics for Historical Network Research

Thèse de doctorat de l'université Paris-Saclay et de Telecom Paris

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Thèse soutenue à Paris-Saclay, le JJ mois AAAA, par

Alexis PISTER

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NNT : 2020UPASA001

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Contents

3 - HSNA Process and Network Modeling

We describe in this chapter the HSNA workflow followed by social historians, to shed light on their process and summarize recurring pitfalls to identify how VA could help them in this process. Specifically, we discuss in depth the network modeling step, as the choice of the network model influence the overall process, especially the possibilities of the analysis. Most HSNA practitioners report on their findings concerning the network they constructed from their sources, but few highlight their process which led to these conclusions from the raw historical documents. Similarly, VA tools always focus on the analysis part, once the network have been constructed, without helping historians in the previous steps. However, the data collection, encoding, and transformation steps are crucial and can introduce lots of bias and distortion on the final data if not done correctly. This is especially true for social history where historical documents can lack structure and can be hard to parse, and where historical claims should be traceable to the original sources. We therefore describe the HSNA workflow split into 5 steps and characterize recurring pitfalls which can occur in each step. We also discuss in depth the network modeling step, as social historians can model their documents with various models which have an impact on the representation of the social relationships, traceability to the documents, and simplicity of usage.

This chapter is an updated version of an article presented at the VIS4DH workshop of the IEEE VIS: Visualization Visual Analytics Conference 2022, and published in IEEE Explore [112]. It was a collaboration with Nicole Dufournaud, Pascal Cristofoli, and my supervisors Christophe Prieur and Jean-Daniel Fekete. I participated in the discussions, elaboration of concepts, and writing of the paper.

3.1 . Context

Tools for social network visualization tend to ignore the context in which the networks are produced, where they come from, and the workflow that led from their origin (e.g., documents, polls, interviews, web scraping) to their network form. Yet, practitioners of social history need to generate many networks from the same documents/sources to visualize and analyze them. In this chapter, after describing and characterizing the workflow of Historical Social Network Analysis [149] from our collaborations with social historians, we explain why and how effective tools for supporting this process should model social networks in multiple steps to support three essential principles: *traceability*, connection to *reality*, and *simplicity*. These principles emerged from joint experiences as historians and computer scientists while collaborating on multiple projects.

Social historians' goal is to characterize socio-economic phenomena and their dynamics in a restricted period and place of interest and to see how individual people of that time lived through those changes. For this, they rely on historical documents such as conversational letters, censuses, and marriage acts. They usually extract qualitative and quantitative information from an identified corpus of documents, to then make conclusions on interesting socio-economic topics such as migrations, business dynamics, education, and kinship. For doing this, historians can apply HSNA methods, by modeling the social relationships between a set of entities—usually individuals—into a network. Historians therefore collect documents, annotate them, construct a network from the annotations that they finally analyze and visualize to validate or find new hypotheses. Unfortunately, the process is often linear, and it is common that, when visualizing their network, historians spot errors and inconsistencies in the annotations that they could have fixed if the process was iterative.

Moreover, historical documents are often complex and the annotation and modeling process can be done in many ways. Several network models have been proposed ranging from simple and specific ones like co-occurrence networks to more general and complex ones such as multilayer networks and knowledge graphs. Simple models allow answering specific questions and are easy to manipulate but are often too simplistic and may distort the information contained in the documents. Moreover, they often break the traceability from the analysis to the original documents, making the communication of findings less reproducible and the process of cleaning the annotations complicated. Indeed, errors and mismatches often occur in the annotation process, for example, due to entity disambiguation problems. On the contrary, too complex models are complicated to visualize and analyze, and historians do not always have the tools to create them properly. In this chapter, we propose to model historical datasets as bipartite multivariate dynamic networks, where both persons and documents are modeled as nodes with attributes. While this model is simple enough for creation and inspection, it allows tracing back the entities of the network to the original sources for a continuous annotation process and still accurately models the social relationships mentioned in the documents. Historians can therefore use this model to simultaneously find errors and inconsistencies in their annotation process—allowing them easier back and forth between the annotation and analysis steps—while starting a first analysis and exploration of the data to answer their sociological questions. The traceability to the original sources also makes the communications of findings more replicable and transparent.

3.2 . Related Work

Since we already elaborated on the related work of SNA, HNR, network modeling, and social network visualization in chapter 2, we only discuss in this section the related work concerning historians' workflow and methodology descriptions.

The essence of the historical discipline is based on a critical approach of sources and involves considering peers' work. Traditional approaches to history often focus on the construction of a narrative, without necessarily adopting a systematic and problematized approach to the exploitation of original sources. Social history and the "Annales School" proposed a new approach to history, by trying to describe and characterize socio-economic phenomena of the past by rigorously extracting information from historical documents and making conclusions from them.

With similar aims, Glaser and Strauss developed the "Grounded Theory" [50] as a methodology for the humanities to build hypotheses and theories by solely studying and categorizing real-world observations, without starting from prior knowledge and predefined categories. Later on in the 1960s, quantitative methods started to be used in history, providing statistical and later computer-supported tools to aid historians in grounding their analysis in mathematical models and results. Unfortunately, the lack of methodology and understanding between the two worlds led to many criticisms by historians pointing to using wrong metrics, simplifying categories, and disconnections between the original documents and analysis [70, 82]. Quantitative history has been showed to be useful when used properly and when not focusing only on numbers, and several books have been published on how to efficiently use statistical methods such as summarizations, correlations, statistical distributions, statistical testing, time series etc. [66, 81]. Similarly, the use of network science for historical aims increased in recent years, and a lot or resources exist on how to use network methods and measures for historical research [72, 80].

However, little work has been done on describing and formalizing the process before the analysis part for a quantitative and network research workflow. Indeed, if it is central to know how to manipulate statistical and network concepts and methods when following this kind of methodology, it is as important if not even more to follow a correct and rigorous workflow to generate the data we plan to analyze beforehand. The process to generate a clean quantitative or network dataset from historical sources is difficult and requires several data acquisition, annotation, and cleaning steps. Social analysts are not always trained on how to do these steps effectivity, which can lead to errors, inconsistencies, and mismatches between the chosen data models and the historical questions [2]. Karila-Cohen and al. provide some advice on how to annotate historical documents with the aim of using quantitative methods [70] and prone that the annotation and analytical processes should not be dispatched between several persons, as both usually influence each other. Dufournaud describes her workflow in depth when studying the socio-economic status of women in France in the 16th and 17th centuries, which she splits into three steps: *data collection*, *data processing*, and *data analysis* [34]. She provides the tools and methodology she used to annotate her data, providing transparency on her historical analysis and methodological resources. Cristofoli discusses the network modeling problem when following an HSNA and highlights the fact that the same historical documents can be modeled in different ways [23]. Historians should be aware of this and choose a network model which fits their analytical

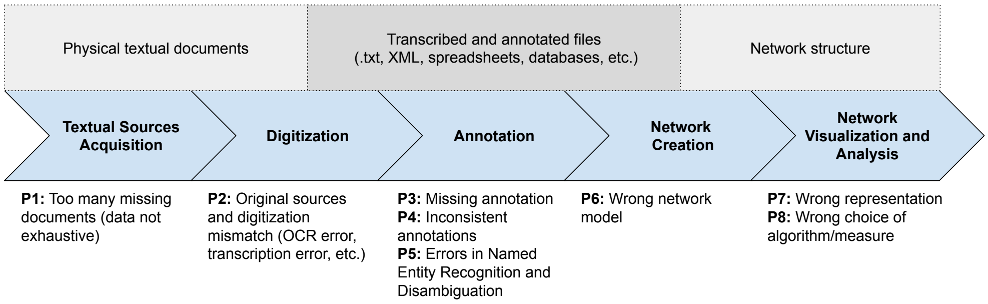


Figure 3.1 – HSNA workflow is split into five steps: textual sources acquisition, digitization, annotation, network creation, network visualization and analysis. We list potential pitfalls for each step.

goals.

3.3 . Historical Social Network Analysis Workflow

From the literature and our own projects of HSNA we conducted during the last years in collaborations with historians, we propose an HSNA workflow divided into 5 steps: *textual sources acquisition*, *digitization*, *annotation*, *network creation*, and finally *visualization and analysis*. The workflow is presented in Figure 3.1 along with potential and recurrent pitfalls.

3.3.1 . Textual Sources Acquisition

Historians' first step is gathering a set of textual historical documents mentioning people with whom they will have social ties. For this, they usually take documents from a specific source—such as a folder from a national or local archive—and restrict them to a period and place that they want to study. They also often restrict themselves to one document type—such as marriage or notary acts—to focus the analysis on one or few types of social relationships that they want to understand in depth. However, one rule of the historian's method is to crosscheck from multiple sources, so an initial corpus is often extended with another set of related sources. Once they restricted their search to a set of documents, a time, and a geographic area, they try to exhaustively find all the documents matching the desired properties, as **missing documents can result in uncertainty in the network structure and therefore the sociological conclusions (P1)**.

3.3.2 . Digitization

Digitization consists in converting the sources into a digital format. This step can be skipped for the most recent periods where many documents have been produced digitally or can be scanned and well digitized through optical character recognition (OCR), allowing to tremendously ease the storage, indexation, and annotation of the documents. However, before mid 20th century, most historical primary sources are stored in archives in paper format and need human work to be digitized. **Mismatches between the original documents and the transcription can occur for old and recent documents (P2)**. However, if OCR tools are more and more efficient in English and highly used languages, historians can work with old documents written in old or extinguished languages and with atypical writings (e.g., Fraktur handwriting and typefaces for German in the early 20th century). Therefore, OCR tools are often unusable in social history and digitization remains an expensive and sometimes highly skilled process.

3.3.3 . Annotation

Annotation is the process of finding and extracting useful information from the documents concerning the persons, their social ties, and any useful information for the historian. This extra information can concern the persons (their age, profession, sex, ethnicity, etc.) and their social relationships (type, date, place). It encompasses named-entity recognition (NER) as well as their resolution. Historians also sometimes annotate information on other entities mentioned in the documents, such as art objects or administrative entities. Usually, historians have a first idea of what they want to annotate in the data as they already explored the documents beforehand and have knowledge of their subject of study, with hypotheses they want to explore. It is however common they can change their mind through the annotation process, by reflecting on what they found in the documents. Unfortunately, this can produce **missing annotations (P3)** and **inconsistent annotations (P4)** at the end of the process if annotators are not careful. This task can also be challenging and the choice of annotations has an impact on the final network. Historians also face ambiguity in the process, as several persons and entities (like cities) can have the same name (homonyms), refer to a place name that has disappeared (street name or city), or to an ambiguous person (e.g., John Doe). They, therefore, have to follow a NER and resolution/disambiguation process to identify entities in the sources and disambiguate them across several documents. Entity resolution has always been a problem in social history—as it is more generally in text analysis, where typical groundwork consists in crossing information about the same entities from different heterogeneous sources. However, errors in the disambiguation process can lead to important distortions in the final network structure and properties [31], e.g, people connected to the wrong "John Doe".

Historians usually carry out this process manually but can also use automated methods and refine the results themselves later. Unfortunately, **errors are common in this step as automated methods do not provide perfect accuracy, nor doing it manually given the lack of global information (P5)**.

The Text Encoding Initiative (TEI) [22] is an XML vocabulary and a set of guidelines typically used to encode and annotate documents, and the events happening in these documents (unclear parts, gaps, mistakes, etc.). It is also used for historical texts and to generate social networks [35, 128]. Unfortunately, the guidelines are not meant to define a canonical annotation and different persons can interpret the guidelines in different ways, leading again to inconsistent annotations of corpora (P4) and to errors or distortions in social networks derived from these annotations.

3.3.4 . Network Creation

Historians construct a network from the annotations of the documents. Usually, all persons mentioned are annotated and will be transformed into network nodes (vertices). Additional information such as their age, profession, and gender can be stored as node attributes. How the network's links are created is not as trivial and can vary from project to project [2]. The most straightforward approach is to create a link between every pair of persons mentioned in one document, thus forming a clique motif. This is a simplistic heuristic as social relationships can be quite complex, involving more than two persons who can have different roles in the relationship. The choice of the network model has a major impact on the future analysis and **may add bias if chosen loosely (P6).** More complex models have been proposed in the literature such as weighted, dynamic, bipartite, and layered networks.

3.3.5 . Network Analysis and Visualization

Once historians have constructed a satisfactory network, they start exploring and analyzing it with visualization and quantitative methods. The final goal of HSNA is to find interesting patterns and link them to social concepts to gain high-level socio-historical insights [43, 149]. Usually, historians start to visualize their network to visually confirm information they know, then to potentially gain new insight with exploration. Representations need to be chosen wisely given the network as lots of techniques and tools exist for social network visualization. **Some insight may be seen only with some specific visualization technique (P7)**. To test or create a new hypothesis, historians typically rely on algorithms and network measures. Lots of network measures have been developed like modularity, centrality, and clustering coefficient that social scientists can leverage to make conclusions [127]. Similarly, social scientists can use data mining algorithms to highlight interesting and potentially hidden structures in the network, e.g. by using clustering algorithms revealing group structures [15]. **However, they have to interpret the results carefully (P8)** as some algorithms act as black boxes and some measures are hard to interpret, with unclear sociological meaning (e.g., centrality). Typically, particular patterns and measures values in the network could have different potential sociological meanings. If we take as an example betweenness centrality which measures the number of times a node appears in the shortest path of every pair of existing nodes, individuals with high values usually highlight positions of power as they communicate with different groups. However, it can also be interpreted as a position of vulnerability in other contexts such as during periods of wars and repressions, as in the study of Polish social movements in the 20th century by Osa [104] where she shows persons with high betweenness centrality values are more targeted for repression in certain periods. Social scientists, therefore, have to be careful when interpreting network measures and take into account the globality of their sources when interpreting the network they constructed.

3.4 . Network modeling and analysis

Historians typically construct one or several networks from their annotated documents that they will visualize and analyze to validate or find new hypotheses. As the processing steps of the workflow are often not transparent (digitization, annotation, network modeling), it can be difficult for the reader of an HSNA study to understand how the network has been constructed, what it represents, and to trace back the network entities to the original sources [34]. Moreover, visualizing the network very often highlights errors and artifacts of the annotations, along with potential mismatches between the network model and the analysis goals. Historians then have to correct or change their annotations, even though it is a very tedious and demanding process to repeatedly switch back and forth between the network and the annotated documents. Several network models make the task harder as they do not directly represent the documents, and it is thus difficult to relate a network entity to a specific document and annotation. Therefore, we believe that more visual analytics tools should support social scientists in annotating and modeling their documents to make the HSNA process less linear by allowing easier back and forth between the annotation, modeling, and visualization steps. Network models satisfying *traceability*, *reality* and *simplicity* properties would mitigate those problems by allowing to navigate more easily between the network and the documents while still modeling well the social relationships mentioned in the sources and being easy enough to visualize and manipulate for analytical and cleaning goals.

3.4.1 . Network Models

Currently, historians use various network models depending on their knowledge of network science, the content of their documents, the schema of their annotations, and the analysis they plan to make. We describe here the most used network models in HSNA along with more recent ones:

- **Simple Networks [149]:** According to their research hypotheses, historians select and merge document information to build a specific relationship between individuals. They analyze this simple network structure with SNA tools and produce network indicators and node-link visualizations. It is often difficult to connect the results to the original sources.
- **Co-occurrence networks [123]:** Only the persons are represented as nodes, and two persons are connected with a link when they are mentioned in the same document (or section). This is a simple model and one of the first to have been used in SNA and HSNA. The major drawback of this model is that it does not take into account the diversity of social relationships, as every link is

identical. It can work well when only one type of social relationship is studied like a friendship network [95]. However, historical documents rarely mention only one type of relationship and this model is thereby very limiting for HSNA.

- **Multiplex Unipartite Networks [38]:** Only the persons are represented as nodes, and links model social ties between two persons. Links can have different types representing different types of social relationships. It allows modeling more complex social relations where people can have various social ties e.g. as parents, friends, and business relationships. However very often several possible representations for the same data exist as projections are often applied to the original documents to get this type of model. One of the main drawbacks of this model is that it creates parallel edges that are hard to visualize.
- **Bipartite (also called 2-mode) Networks [58] :** Nodes can have two types: persons and documents in this network model. A link refers to a mention of a person in a document and can thus only occur between persons and documents nodes. Usually, links are not typed and only encode mentions. More recent analyses in HSNA encode the *roles* of the persons in the documents as link types [25]. This network model is more aligned with the original sources and allows following an analysis through the original documents themselves and not through concepts. For example, the GEDCOM format introduces the concept of "family" that ties together a husband, spouse, and children with different link types. However, the concept of family can have different meanings across time and cultures, meaning that GEDCOM adds a conceptual layer instead of grounding the network to concrete traceable documents and events (e.g., no marriage but birth certificates).
- **Multilayer Networks [87]:** in these networks, each node (vertex) is associated with a *layer* l and becomes a pair (v, l), allowing to connect vertices inside a layer or between layers. These advanced networks have received attention from sociologists [26] and historians [144], but they are complex. The meaning of a layer varies from one application to another; it can be time (years), type of documents, the origin of sources, etc. They, therefore, offer many (too many) options for modeling a corpus, and visualizing it, with no generic system to support historians for taming their high complexity.
- **Knowledge Graphs (KG) [65]:** they represent knowledge as triples (S, P, O) where S is a *subject*, P is a *predicate*, and O is an *object*. Everything is encoded with these triples using controlled vocabularies of predicates and rules known as *ontologies*. KG is popular for encoding knowledge on the web, including historical knowledge. However, it is notoriously complex to encode documents using KG due to the complexity of the format and the wide choice of possible ontologies. Most historians are unable to understand KG and even less to use it for annotating a corpus. Since KG are generic, they need complex transformations to be visualized, with no generic system to support historians in taming their high complexity.

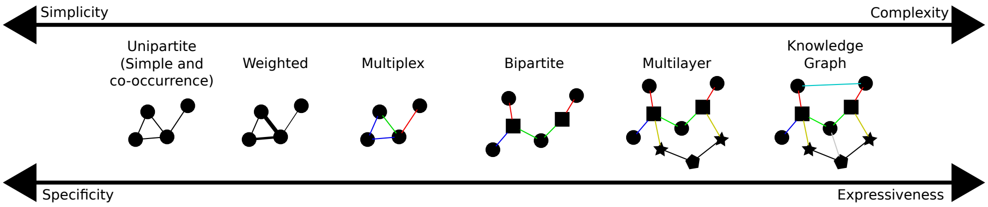


Figure 3.2 – Schematic representations of Different network models used for analyzing historical documents, ordered by complexity and expressiveness

We argue that historians should aim to model their networks simply enough to be manipulated by them, in a way that entities can be traced back to the sources, and expressive enough to model accurately the social reality of the documents—i.e., having those three properties: *simplicity*, *traceability*, and *reality*.

Currently, most digital historical projects use unipartite networks (simple, co-occurrence, and multiplex) that are simple and allow answering specific questions, but they do not capture all the complexity of the documents, and social scientists may miss important patterns. For example, modeling only co-occurrences of persons in documents remove the variety of social relationships these mentions can refer to. Moreover, since documents are not explicit in the unipartite model, it is hard to trace the network entities back to the sources: the traceability property is not satisfied. On the other side, multilayer networks and KG allow to model documents as entities and express complex relationships between various other entities they mention. These models can be very expressive but are challenging to use for historians, especially without guidelines; without *simplicity*, the *traceability* and *reality* properties can be hard to achieve. Moreover, they are difficult to visualize and analyze, especially for social scientists.

Figure 3.2 shows a schematic representation of the different network models, ranked on simplicity/complexity and specificity/expressiveness axis.

3.4.2 . Bipartite Multivariate Dynamic Social Network

Historical documents are well modeled by bipartite multivariate dynamic networks with roles, which have the following properties:

Bipartite: There are **two types of nodes**, persons and documents (or events). An event, such as a marriage, is most of the time witnessed by a document, and we refer to them interchangeably as events and documents. Events considered in the network can be of the same sub-type, such as contracts, or of multiple subtypes, e.g. for genealogy: *birth certificates*, *death certificates*.

Links and Roles: A link models the mention of a person in a document. **Each link has a type corresponding to the role of the person in the document**. For a marriage act, the roles include *wife*, *husband*, *witness*. This is a key aspect of our model since it clarifies the relationship between the persons within an event.

In contrast, Jigsaw [136] does not consider the roles.

Multivariate: Each entity of the model can have attributes, that give additional information. Person nodes are referenced by a key that reflects the disambiguation process. They can have general information (standardized name, gender, birth date). Documents are also identified by a key, e.g., an archive reference. The associated event can have a date, sometimes a location, and potentially other information. Links can also carry information to describe contextual properties (activity, residence, etc.).

Geolocated: Events should have a location when it makes sense, ideally with the longitude and latitude.

Dynamic: Events are always dated. We rely on this date since it encodes the social dynamics of the network.

One of the main benefits of this model is that the document nodes represent both the physical documents and the events the documents refer to. For example, concerning marriage acts, the document nodes represent both the physical documents with their texts and also the marriage events with their characteristics modeled as attributes (time, location, etc.). Therefore, social historians can use this model to store, process, and clean their original documents and follow an analytical workflow with the same representation. This model is *simple* enough to manipulate and visualize for historians and allows tracing back every entity of the network to the documents according to the *traceability* principle. Still, the network preserves the *reality* of the social relationships mentioned in the sources as no projection or transformation is applied.

3.4.3 . Examples

We discussed with four experienced historians collaborators at different steps of their HNSA workflow about their annotation process and how they wanted to model their data into a network. They all work on semi-structured historic documents, mentioning complex relationships. We provide more details in the following:

1. Analysis of the social dynamics from **construction contracts in Italy in the 18$^{\text{th}}$ century [25, 101].** The corpus is made of contracts for different types of constructions in the Piedmont area in Italy. People are mentioned under three different roles: *Associates* who are in charge of the construction, *Guarantors* who bring financial guarantees, and *Approvers*, who vouch for the guarantors. Documents contain information about the building site, the type and materials of constructions, and the origin of the people.
2. Analysis of migrations from the **genealogy of a french family between the 17$^{\text{th}}$–20$^{\text{th}}$ centuries** [unpublished work]. The corpus is made of family trees referring to several document/event types: birth and death certificates, marriage acts, military records, and census reports. The roles are different for each event type and consist of *children, father, mother* for the birth events, *deceased* for the death event, *spouse* and *witnesses* for the marriages, and *family member*s for the census events.

3. Analysis of migrations from Spain to Argentina through the **marriage acts at Buenos Aires in the 17–19$^{\text{th}}$ centuries [96, 122].** The corpus is made of summaries of marriage records that mention the spouses and the witnesses of the wedding. The origin, date of birth, and parents' names are specified for both spouses.
4. Socio-political analysis of **migration of ethnic Germans from communist Romania to West Germany in the 20th century (ongoing work) [32].** The corpus is made of administrative forms that mention persons requesting to migrate, along with the persons they want to join, and the administrative persons of the ministry in charge of the forms. The family members of the aspiring migrants are also mentioned in the forms, with their respective dates of birth.

We compare what would be the resulting networks for the three first examples (the example #4 is still in the phase of data acquisition) when modeling the data with the three most frequently used network models in HSNA: co-occurrence, multiplex unipartite, and bipartite networks. We also encode important information from the document as network attributes. We do this for one given document for each dataset. The results are shown in Table 3.1.

As shown by Cristofoli [23], we can clearly see the co-occurrence model removes the complexity of the social relationships and only shows an abstract "proximity" between individuals. Unipartite projections allow producing meaningful networks which model well the diversity of relations that can link several people. It especially models well simple relationships such as parenting ones as in example #2. However, it produces distortions for more complex relationships involving more than two persons, as in example #1 where people can either be mentioned as associates, guarantors, and approbators in the documents. Associates should probably be linked together with *associate* links, but the *guarantors* and *approbators* relationships are more complex to model. Approbators could be linked to the associates, the guarantors, or both. The three ways of modeling this type of relationship make sense but can lead to very different network shapes and analysis results. Historians thus have to decide on a transformation among several possibilities, which will probably distort the social reality of the relationships.

Moreover, projections add ambiguity in retrospect of the original documents, as it becomes impossible to trace back one link to one specific document, as the same link could potentially refer to several ones [23].

Finally, these examples show that when working with multivariate networks, using projections to create unipartite networks brings a duplication of information. Indeed, if a document mentions information like a date that we model as an attribute, we can store it as a document node attribute using a bipartite model. However, when projecting the network this information appears in the links as many times as there are persons mentioned in the document minus one and often more. For example, in the example #1 in Table 3.1 the time is stored in $\sum_{i=1}^{4} i = 10$

links in the co-occurrence model and in 9 links in the multiplex unipartite model while it is only stored once as a document node attribute in the bipartite model.

3.5 . Applications

Several tools have been designed for visualizing dynamic bipartite networks that can also be considered dynamic hypergraphs [108, 142], but few incorporate attributes. Moreover, the vast majority of visual analytics tools are solely focused on the analytical part of the data, meaning that the link between the original documents and the hypergraph abstraction is often broken. Social scientists therefore always have to do many back and forth between the visual analytics tools and their original documents and the annotation/modeling processes. More visual analytical tools should thus incorporate the textual documents in their data model similarly to Jigsaw [136], as it would allow tracing the entities of the network back to the original documents more easily. Mechanisms to clean/modify the annotations and reflects on the network modeling process directly in the analytical environment could also ease the social scientists' workflow loop. It would allow them to directly clean errors and inconsistencies in the annotations and propagate them in the visual analysis workflow. For example, the Vistorian [128] now lets users modify and clean their data in a table format if they see errors or inconsistencies.

3.6 . Discussion

Most tools for social network visualization focus solely on the visualization and analysis steps, without considering the whole historical data analysis process, preventing researchers from going back to the original source, and supporting the social analyst in the annotation and modeling steps. We think visual analytics tools helping social scientists annotate and model their data with *reality*, *traceability*, and *simplicity* principles in mind are essential to conducting socio-historical inquiries with limited friction, realistic training, and scientific transparency. Concerning the network modeling step, bipartite multivariate dynamic networks model well the majority of structured historical documents such as marriage acts, birth certificates, and business contracts as these documents refer to specific events (birth, marriage, transaction, etc). The document nodes, therefore, represent both the textual documents and the specific events. This dual representation works well for semi-structured documents but could be more limiting for other more literary documents. Moreover, structured documents can also provide information about other relationships not directly linked to the main event. For example, marriage acts sometimes refer to the place and date of birth of the spouses with the names of the parents. This information relates to the birth of the spouses and not the marriage specifically. In that case, social historians can either ignore this type of information in the annotation process or encode it with specific roles (*husband's*

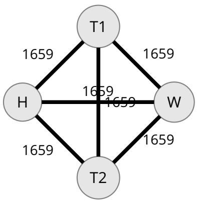
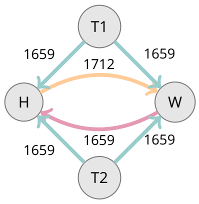
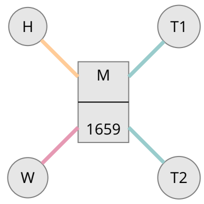
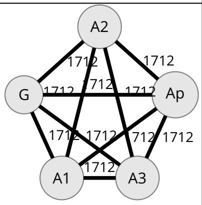
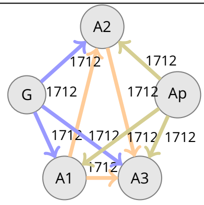
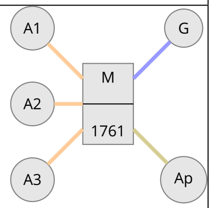
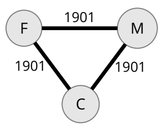
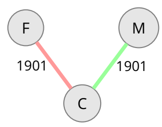
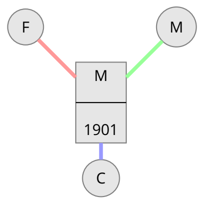
<table>
<tr><th>Original Document</th><th>Co-occurrence</th><th>Unipartite representation</th><th>Bipartite</th></tr>
<tr>
<td>20-4-1659 : Capitán Alonso MUÑOZ de GADEA , con Da. Francisca CABRAL LEAL de AYALA . Ts.: Agustín Gayoso , y Juan Guerrero. Al margen: "fue Oficial Real" , (f. 9v).
Husband Wife Witness</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1712: Construction of a church in Torino. Associates: Bellotto G, Bello P.M, Bello G. Guarantor: Astrano G.A. Approbator: Corte A.
Associate Guarantor Approbator</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Du dix-neuf fevrier mil huit cent quatre-vingt quatre, à six heures du soir. Acte de naissance de Dufournaud Alexis, enfant de sexe masculin né le dix-neuf février, à deux heures du soir au village de Grudet, commune de Saint Symphorien, des mariés Dufournaud Alexis , cultivateur colon, âgé de trente ans , et Marie Pardonnaud, sans profession, agée de vingt-six ans , demeurant au village de Grudet, dite commune de Saint-Symphorien. [...]
Father Mother Child</td>
<td></td>
<td></td>
<td></td>
</tr>
</table>

Table 3.1 – Resulting networks using different models produced by one document of the examples detailed in §3.4.3: co-occurrence, unipartite and bipartite models. The first column shows the partial transcription of real documents. Colors represent annotations concerning the persons mentioned, their roles, and attributes. Underline refer to information related to the events and which can be encoded as document/event attributes. H: Husband, W: wife, T: Witness, M: Marriage, A_N: Associate, G: Guarantor, Ap: Approbator, C: Construction, F: Father, M: Mother, C: Child.

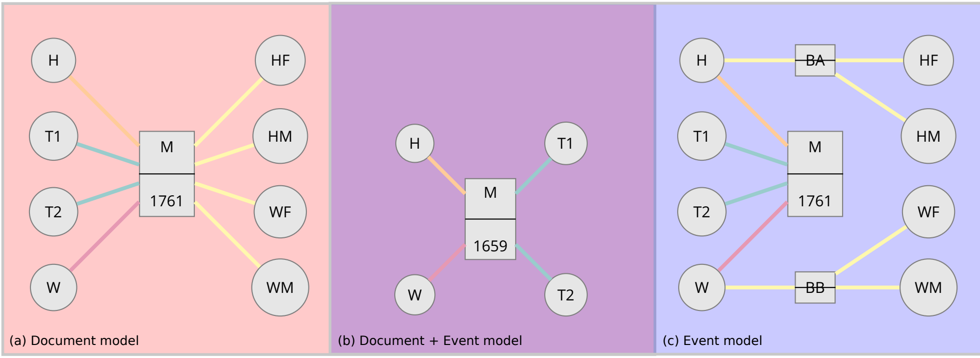


Figure 3.3 – bipartite multivariate dynamic network modeling for two cases of marriage acts of example #3. Some marriage acts mention the parents of the spouses, which is a relationship different than the marriage in itself. This case can be modeled using a document model (a) or an event model (c) by 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.

father and *wife's father* for example), thus turning the network into a model of the documents only, and not events. We show what would look like the resulting networks Figure 3.3for the two cases where marriage acts mention birth information and the case where only marriage-related information is present in the document.

3.7 . Conclusion

HSNA is a complex process that starts by collecting historical documents and ends with elaborating high-level sociological conclusions. Historians support their conclusions by modeling individuals' social relationships extracted from the documents and analyzing the resulting networks. We tried to shed light on this process by dividing it into 5 steps and describing recurrent pitfalls we encountered in our projects and collaborations. More importantly, we think this process should be done following the principles of *reality*, *traceability*, and *simplicity*, to avoid biasing the analysis, allowing to go back to the original source at any point of the workflow, and using models and methods simple and powerful enough for social scientists. Visual analytics software designed for HSNA should consider those principles to provide tools allowing to follow non-biased and reproducible analysis starting from the raw documents while supporting historians in going back and forth more easily between the annotation and analysis/visualization steps. We discussed the network modeling process in depth and claim that bipartite multivariate dynamic networks satisfies those three core principles, letting historians both wrangle their data and characterize sociological phenomena using a common model and visual representation. Therefore, using this model VA interfaces could help social scientists manage and analyze their data starting at the data acquisition and annotations steps instead on focusing on the analysis only, while providing efficient representations of the data for analysis and exploration. We explore what could be such VA interfaces in the two next chapters.

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