Research Plan

Factors of social change during the European Reformation
A statistical network approach

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1 Introduction

Within this thesis we aim to statistically extract *exemplary* factors which drove social change during the Reformation. This thesis will *not* provide an overarching analysis of social change during the Reformation in general. The methodology of this thesis will use inferential statistics with a focus on network models.

Why study social change during the Reformation? The Reformation was a significant transformative movement of society in early modern Europe. Initiated as a renewal movement against the established Catholic Church, the Reformation eventually gave rise to several competitive protestant denominations, such as Lutheranism and Calvinism (Kaufmann 2017). The Reformation also strengthened polycentric governing structures and increased participation rights of citizens. (Kaufmann 2017).

These developments illustrate *social change*, a change in social relations leading to transformations of social institutions that often have profound long-term consequences for society (Haferkamp and Smelser 1992). Besides the Reformation, classic examples of social change include the Industrial Revolution as well as Women's and Civil Rights Movements. Within this thesis, we are interested in how certain factors drive social change, such as political events or conflicts between social groups.

These driving factors also exist in our modern world. They affect current societal challenges, such as climate change and social inequality, which may in turn redefine our social relations. Studying social change may therefore help to address these present challenges. So why do we study social change in the distant past instead? We provide three reasons. First, because it is easier to judge the importance of changes within a historical context. Second, access to data records about the distant past are not restricted. The data are free of charge because no business interests are involved. Personal data of historical figures are available because privacy laws do not apply. Secret deals can be accessed because non-disclosure agreements do not pertain. Third, the vast body of qualitative knowledge available about the Reformation facilitates the interpretation of our quantitative analysis of social change.

How have we studied the Reformation so far? The majority of previous research about the Reformation has applied *qualitative methods*, which deal with non-numeric data like text and images (Schindling and Ziegler 1996; Burkhardt 2002; Kaufmann 2017; Strohm 2017). In practice, this requires the historian to first read primary and secondary sources about the Reformation. Then, she reconstructs the historical context by connecting the individual sources and by reasoning about them. Eventually, she publishes her thoughts as another secondary text source.

Although this methodology allows for very detailed analyses, it is restricted to small data sets and cannot test theories in a systematic way. Humans have limited processing power and therefore cannot consistently analyse thousands of data points. As a consequence, qualitative analyses apply a microscopic approach where individual cases are studied in isolation. Moreover, we are still unable to formalise the human reasoning steps involved in qualitative processing of historical sources. As a consequence, we cannot reproduce the steps historians took to develop a theory and therefore cannot test this theory in a systematic way.

In response, the upcoming research field of the *Digital Humanities* has started to digitise historical sources, which enables computers to conduct formalised analyses on large data sets (Warwick et al. 2012). So far, Reformation-researchers have pre-eminently used *descriptive statistics* to exploit these new opportunities (Gamper et al. 2015; Brughmans et al. 2016; Düring et al. 2016; Skories 2017; Hotson and Wallnig 2019). The researchers summarise numeric data from a data sample, such as its central tendency and variability, and then draw conclusions from this sample to the underlying historical context of interest, i.e. the Reformation. For example, a data sample from the Reformation may refer to all letters written by reformers that are accessible today. The central tendency could then refer to the mean number of letters per reformer and the variability to the extent with which these numbers deviate from their mean. Researchers have then used these computed metrics to gain insights into letter correspondence during the Reformation in general.

What are the limitations of current methods to study the Reformation? When studying the Reformation, we would like to make statements about *all* entities that represent (aspects of) the Reformation. These entities could, for instance, correspond to all people having exchanged letters between 1500 and 1648. However, this *population* is inaccessible because of restrictions in data collection. In practice, we, therefore, study a *sample*, a selection of entities from the population. For instance, all people who exchanged letters between 1500 and 1648 *and* whose letter records are today publicly accessible.

The problem with qualitative methods and descriptive statistics is that they can exclusively make statements about such a data sample. What we want instead is to generalise from one sample to the population. In order to address the need for generalisability, researchers have primarily focused on obtaining more representative data samples by generating larger data sets. Along the lines of 'bigger data is better'. Unfortunately, no historical data set will ever be representative since data are not randomly collected but selected upon availability. This availability is influenced by historical processes, priorities of musea and archives and other non-random factors (see selection bias in 'Adressing pecularities of the data' in section 2.1). Qualitative methods and descriptive statistics offer no systematic way to quantify how unrepresentative the data are of the population and its effect on the analysis.

1.1 Research gap

Previous studies about the Reformation have mainly used qualitative methods and descriptive statistics. Qualitative methods use a microscopic approach which focuses on individual case studies in isolation. This neglects the fact that individual cases are interdependent and that their connection patterns can provide a novel perspective on the Reformation. The macroscopic approach takes these connection patterns into account. Descriptive statistics can take a microscopic or a macroscopic approach but their findings are always restricted to the observed data sample.

What is missing is a macroscopic approach that is generalisable from the data sample to the population and allows us to measure the error made during this generalisation.

In this thesis, we will apply models from inferential statistics to draw conclusions from the sample to the population and to quantify the error in this process. Moreover, we will explore the use of network models for a macroscopic approach to the Reformation. Last, we will generate rich and structured data sets on letter correspondence between reformers and geo-political characteristics of the political system of Europe in the 16th century.

2 From letter collections to data

Why focus on relational data? *Relational data* specify and quantify the type of a relationship between two or more entities, such as the number of messages two communication partners exchange. Depending on the type of a relationship, the relation between the entities can be directed (e.g. sender and receiver of a message) or undirected (e.g. being married).

In a social context, relational data can represent social interactions or social relations between actors. *Social interactions* are temporally limited, possibly repeatable events between two actors, such as conversations, trading of goods, and exchange of letters. In contrast, *social relations* are long-lasting connections between two actors such as kinship or employment relationship.

In order for behavioural patterns to spread and establish within a population, social change requires behaviour in which actors affect each other. This behaviour is due to social interactions and relations (Homans 1958). Studying those, therefore, provides a promising approach to understand social change. Besides relational data, non-relational data may also correspond to driving factors of social change. Examples include time series of events (e.g. years of famines), individual characteristics of actors (e.g. age), or the spatial distribution of quantities (e.g. wealthy vs poor geographic areas).

2.1 The letter correspondence data set

Descriptives reveal low data integrity The starting point of this PhD project is a relational data set consisting of $\approx 20,000$ letters sent and received between $\approx 2,500$ European reformers in the period between 1510 until 1575. The term 'letters of reformers' is slightly misleading since our correspondents are not exclusively theologians who fought for the Reformation. Our data also include noblemen (e.g. dukes, princes, the Emperor), catholics (e.g. bishops, monks), humanists, pressmen, university lecturers, and other ‘professions’ (technically speaking an undefined concept in the 16th century). These actors may or may not have sympathised with reformist ideas or changed their supported side over the course of time. This rich diversity of correspondents exemplifies how the Reformation affected all sorts of social situations. For the sake of simplicity ‘reformers’ will be used as an umbrella term to refer to all correspondents in the data set.

For each letter, we extracted its meta-data and stored them in a Postgres database. Our extracted meta-data include the following attributes: name of sender and receiver, sending and receiving location, sending and receiving date, the language of the letter text, and the letter text itself. Data integrity varies heavily across attributes, as the proportion of missing values relative to the total number of letters show:

- Sender name: 0.002
- Receiver name: 0.0002
- Sending location: 0.080
- Receiving location: 0.516
- Sending date: 0.0002
- Language: 0.815
- Letter text: 0.816

Note, that these numbers are an optimistic estimate since we only checked for empty entries. It may well be the case that an entry is provided but does not represent a meaningful value for the data attribute in question. For example, according to our definition of missing values, ‘xxx’ would be a valid entry but does not carry any meaning for a meta-data attribute.

Dealing with fragmented data acquisition Collecting letter correspondence data from the Reformation is highly challenging. Different types of data formats have to be considered (e.g. online, offline) which do not share a consistent way of structuring and accessing the data. As a consequence, a particular data collection method has to be designed and implemented for each data source. Also, data access is often restricted by ownership rights of the respective database managers. Thus, even though our letter correspondence data are mainly already digitised, their acquisition is more tedious than modern digital data (e.g. social media), which usually provide an API for data access.

For this PhD thesis, we consider three main types of data sources: First, 19,430 letters were collected by crawling public online repositories which published the partial or complete letter editions of specific reformers. In this way we received 3,886 letters from Martin Luther (ProQuest-LLC 2015), 8,854 from Philipp Melanchthon (Mundhenk 2019b), 929 from Ulrich Zwingli (Moser 2016), 3,028 from Heinrich Bullinger (Bodenmann 2016), 991 from Martin Bucer (Friedrich 2018), 1,740 from Oswald Myconius (Wallraff 2016), and 96 from Andreas Karlstadt (Kaufmann 2012).

Second, some letter editions were manually digitised by historians and kindly provided to us. Burnett (2019) provided 515 letters from Johannes Oecolampadius (Staehelin 1927) and 1943 letters from Joachim Vadian (Arbenz and Wartmann 1884-1913). Mundhenk (2019a) provided additional 8,670 letters from Philipp Melanchthon. These manually assembled letter editions also include data on letters that went missing over time but were mentioned in available letters (“... as I wrote to you in May ...”).

Third, we take into account published print letter editions. These editions have not been digitised yet, or their digitised version is inaccessible to us. Since these print editions are either very large or provide insufficient summaries about their data, it is often difficult to estimate the exact number of letters that these editions include. We identified the following letter editions and provide estimates for the number of letters in brackets: The catalogue of letters in the 16th and 17th century contains letters from several lesser-known reformers and people of public life ($\approx 3,300$) (Elsmann 2015). Johannes Calvin ($\approx 5,000$) (Baum 1863-1900), Andreas Osiander (≈ 450) (Seebaß 2017), and Johannes Gropper (≈ 500) (Braunisch 2006), as well as Johann Jakob Grynaeus ($\approx 4,300$), Simon Sulzer (≈ 760), Matthias Erb (≈ 587), Daniel Tossanus (≈ 254), Amandus Polanus von Polansdorf ($\approx 1,000$) (*Verbund Handschriften - Archive - Nachlässe* 2011; *e-manuscripta* 2013; *Universitätsbibliothek Basel* 2019), and eventually unpublished letters by Bullinger ($\approx 12,000$) (Bodenmann 2019). Moreover, we identified letter editions of several reformers where we were unable to estimate the number of letters: Rudolf Gwalter, Johannes Eck, and Joachim Camerarius (Wilhelmi 2019).

Since these print editions contain letters of some very influential reformers, we assume that they will enrich the correspondence network. We, therefore, started to digitise these data ourselves by running an *optical character recognition* (OCR) on scans of the letter editions. This OCR was run successfully for the Bullinger data. Processing the remaining print editions, in the same way, will not be the priority of this PhD project. However, if additional time is available, it will be spent on digitising those letter data.

Addressing peculiarities of the data In the following, we describe four characteristics of our letter correspondence data that are especially challenging to deal with. First, as with any historical data set we deal with *observational data*, i.e. we passively recorded signals (letters) we found. In our case this complicates the analysis. (1) We cannot easily manipulate the data and test for the effect of some treatment like *experimental data* would allow us to (e.g. testing the effect of a drug). (2) We cannot influence the sampling process meaning that the letters in our data may not be representative for the population of all letters that have been sent during the Reformation. For example, our data contain more letters of 'prominent' reformers, such as Martin Luther, compared to lesser-known reformers. By only concentrating the analysis on the reformers who made it past some selection process, we will be subject to the *selection bias*.

Second, we deal with *unobserved data*, i.e. data that are unavailable for analysis but correspond to events or processes that have taken place in the real world.[1] With respect to the letter correspondence data, unobserved data refer to (1) letters that have been sent between reformers but which are not in our data set and (2) reformers who have exchanged letters but are not in our data set. This can have several reasons. Letters might have been destroyed or went missing over time, they might be part of inaccessible collections (e.g. Vatikan library), or they have not been digitised yet. When dealing with unobserved data, we have to be aware of the selection bias again.

Third, our data are ambiguous as reformers, locations and dates do not refer to unique entities. Since unique names were not established in the 16th century, people used different spellings and also completely different names to refer to themselves. Martin Luther, for example, was known as 'Ludder', 'Ludher', 'Martin from the Wartburg', and 'frater Martin'. A similar issue arises for the sending and receiving locations. Sending dates are often not provided in a day-month-year format but refer to several possible dates when the exact timestamp can not be determined. Although these ambiguous data are the most accurate presentation of historical knowledge, they are unsuitable to perform statistical analyses.

Fourth, our data are subject to uncertainty since manipulations and errors have likely occurred during the data generation chain. For example, during copying of the original letter source, during the transcription of it (historians editing text professionally), or during entering letter data manually into databases. Since we rely on the editorial work of historians and lack background knowledge to check the data for inconsistencies, we leave this potential uncertainty issues untreated.

High necessity for pre-processing *Pre-processing* involves screening the data for quality issues before the analysis. Due to the inconsistencies in data generation and acquisition, this task takes up many resources. The major steps in the case of the letter correspondence data involve disambiguating sender and receiver names, locations, and dates. First, aliases of sender and receiver names had to be matched to the same unique person. We accomplished this name-matching by computing the *editing distance* between two different names, i.e. the number of characters that need to change in one name to receive the second name. If it was smaller than three characters, the two names were matched to the same person. In the other cases, the two names

[1] We explicitly use the term 'unobserved' data rather than the more intuitive expression 'missing' data since missing supposes a sense of completeness meaning that we know which specific letters are missing.

were presented to a historian who manually disambiguated the two names. This pre-processing step is fully completed.

Second, sending and receiving locations had to be matched to a unique geo-location (longitude and latitude). The major challenges included spelling mistakes ('Base' instead of 'Basel'), homographs (words that are spelt the same but have different meanings like the cities of 'Frankfurt' where one is located in the South-West the other in the North-East of Germany), and similar but nonidentical names of different locations ('Wittenberg' vs 'Wittenberge'). Based on the location names in the raw data, we assigned geo-locations with the GoogleMaps API (Google 2019). We then plotted the received geo-locations on a map and corrected outliers manually, such as locations outside of Europe (e.g. 'base' was mapped to a military base in Oklahoma, US). We then conducted random spot tests and checked whether the assigned geo-locations matches the location name mentioned in the letter. This pre-processing step is completed but requires some final checks.

Third, sending dates are often imprecise and refer to several possible dates. Examples include a selection of dates ('1st June 1520 or 1st July 1520'), a reference to a cutoff date ('before 1st June 1520'), or a period ('June 1520'). In order to disambiguate these dates, we defined hardcoded rules that mapped patterns in ambiguous dates to exact dates. For example, if several dates or a period were given, a date was chosen at random among all possible dates. If a cutoff point was given, we matched keywords (e.g. prepositions and holidays like Easter) to fixed date ranges and randomly sampled from them. This pre-processing step is completed but requires some final checks.

Feature engineering *Feature engineering* is the process of creating new data attributes by using domain knowledge and combining existing attributes. Data features and data attributes are synonyms. In this PhD project, we require feature engineering to construct measures for relations between and properties of reformers or other entities, such as political territories, that are potential driving factors of social change. Coming up with relevant data features, constructing them, validating them and integrating them with the original letter correspondence data are non-trivial tasks that require a large amount of interdisciplinary knowledge.

Until now, we engineered three major features. If required more will follow in the future. The first one is the geographic distance between reformers. We defined it as the modern walking distance between the sending and the receiving location of a letter between two reformers and computed it with the GoogleMaps API (Google 2019). We chose the walking distance because it represents the actual travel route of a letter. Since we assume the modern inter-city footpaths to follow ancient ones, walking distances in the 16th century can be well approximated with today's walking distances.

The second feature is a reformer-specific feature which maps reformers to territories. These territories correspond to administrative units in the Holy Roman Empire (HRE), a territorial state in central Europe in the 16th century. The rulers of the individual territories had large spheres of influence relative to the Emperor of the HRE. For example, each territory ruler imposed his personal laws on his subjects, so it mattered in which HRE territory people were located.

Since our raw letter correspondence data only contain information about the sending and receiving town of reformers but not the corresponding territory, we first constructed a territory-specific data set. The starting point was a modern colour-coded map which showed the territories of the HRE in 1547 (Ackermann et al. 2011). We vectorised this map, meaning that we extracted the geo-coordinates of the border of each territory as a polygon. In a subsequent step, we crawled the Wikipedia pages of HRE territories in order to receive territory-specific attributes, such as name, type of rule, and - very important - a geo-coordinate. Next, we merged the vectorised map data with the Wikipedia data by matching territories to polygons when the geo-coordinate of the territory lay within the polygon. This process is called *spatial join*. In order to match reformers to territories, we approximated the whereabouts of a reformer by his sending and receiving locations. We then performed another spatial join where we matched these whereabouts to the vectorised map data. The result of this feature engineering process is two-fold: First, we created reformer-specific attributes by mapping territory-specific attributes to reformers. This mapping was done for territory names, and the next engineered feature exemplifies it for religious ideology. Second, we created a territory-specific data set which can be enriched with all kinds of attributes about the territories. We can test these attributes as environmental driving factors of social change.

For the third engineered feature, we assign religious ideologies to reformers. As the rise of several competitive protestant denominations during the Reformation indicates, reformers supported different religious ideologies and often switched their preferences throughout their lives. The different ideologies are important since they contributed to the division of the Catholic Church.

In order to automatically infer the religious ideology a reformer supported at a particular time, we apply the following assumption: Given that territorial rulers determined the denomination of their subjects and dissenters were often prosecuted (Burkhardt 2002), it was dangerous for reformers to stay in a territory whose official denomination they did not support. Thus, reformers are expected to move to territories whose official denomination matches their religious ideology. The official denomination of territories is part of the territory-specific data set that was described above. Thus, by matching reformer to territories, they can be automatically matched to a religious ideology. Whether this match and therefore also its underlying assumption make sense has to be assessed in a validation procedure.

3 Network models

3.1 Definition and motivation

A *system* is a group of interacting or interrelated entities that form a unified whole. For example, reformers writing letters to each other during the Reformation form a system. So do neurons and synapses in the brain, routers and cables of the internet, or humans forming friendships. A *network* is a simplified representation of a system capturing the system's connection patterns or *topology*, i.e. who interacts with whom (Newman 2012). This is accomplished by reducing the system components to points, the *nodes*, which are interconnected by lines, the *edges*.

Studying individual components (e.g. reformers) or individual connections (e.g. letters) of a system provides a microscopic perspective since these analyses can be done in isolation without considering the rest of the system. In contrast, networks offer a macroscopic perspective as they allow to study the whole system as one entity. This property is useful since the connection pattern of a system has been shown to influence its behaviour (e.g. the connections in a friendship network affect how people form opinions) (Newman 2012).

Networks can be built from all forms of relational data. This property makes them very suitable for our letter correspondence data. Depending on the nature of the connections between the system components, the following properties of networks can be defined. *Directionality:* In *directed networks* edges have an assigned direction and therefore distinguish between a sending and a receiving node (e.g. reformers exchanging letters). In *undirected networks* edges are bidirectional (e.g. reformers supporting the same religious ideology). *Edge weight: Edge-weighted networks* have weights associated with their edges. The weights represent the strength of a connection (e.g. amount of emotional content in a letter). *Unweighted networks* have no edge weights meaning that all edges are equally strong. *Edge count:* In a *multi-edge network* several edges can exist between one pair of nodes indicating the number of connections. This is only possible if edges represent interactions, such as reformers exchanging several letters. A *binary network* only allows one or zero edges between nodes. This is used to represent relations (e.g. being friends).

3.2 Current state of research

The use of networks in historical research has started to develop as a separate methodological branch, *historical network research* (HNR), only over the last decade (Brixler 2015). The spectrum of HNR usage is very diverse and ranges from qualitative, actor-orientated approaches which describe actors' stories and the networks that emerge from them to quantitative methods which capture macroscopic network phenomena (Gamper 2015b). In the following we provide an overview of quantitative network methods.

Aggregated networks *Aggregated networks* represent the most simple network model where all available nodes and edges are mapped to a network simultaneously. Thus, the place and time at which interactions occurred as well as distinctions in their types are not taken into account. The most straightforward approach of analysis quantifies aspects of the aggregated network topology. For this, a pool of established measures exists. *Centrality measures* indicate how important nodes are. They come in different flavours, such as *betweenness centrality*, the extent to which a node connects two groups; *closeness centrality*, how many edges separate a node from the other nodes; *degree centrality*, the number of edges connecting to a node. The *clustering coefficient* measures the density of a network. *Community detection algorithms* determine whether some groups of nodes are more connected than others. *Assortativity* indicates whether nodes rather connect to similar nodes (e.g. nodes being connected to the same number of neighbouring nodes) or to dissimilar nodes.

Previous HNR studies have mainly concentrated on relating those aggregated topological network measures to social relations or characteristics of historical actors. For example, Padget and Ansell (1993) found that the Medici in 15th century Italy had a high betweenness centrality in the network of economic and marriage relations because they never married economic partners nor traded with their spouses' families. In this way, they could play off parties against each other and control the spread of knowledge (Gamper 2015a). R. Ahnert and S. E. Ahnert (2014) mapped the degree centralities of English reformers in the 16th century to their social role and found that martyrs wrote more letters than non-martyrs as the former were often imprisoned, which reduced personal contacts. Van Den Heuvel et al. (2016) discovered that personal and professional relationships between letter correspondents in early modern Europe were associated with the same amount of reciprocity in the network. This finding is presumably because the two types of relationship trigger reciprocity for different reasons: out of trust (personal) and duty (professional). Deicke (2017) mapped types of network triads to types of conflicts between European reformers in the 16th century. Results showed that person-centred conflicts manifest in local star-like network patterns whereas issue-centred conflicts correspond to denser local network structures with larger reciprocity.

In sum, these examples show how topological measures can be applied to individual aggregated networks and how they are eventually used to draw conclusions about the real-world historical system under study. This procedure is problematic for two reasons. First, since we built the networks from a data sample of the real-world system, we have incomplete knowledge about the network topology. This incomplete knowledge may be due to unobserved data or because our data accidentally capture random effects rather than an actual social mechanism that explains the underlying system (Nanumyan 2018). We, therefore, cannot directly reason from the individual network to the real-world system. This is a general problem in network science and not specific to HNR (Wider et al. 2016). Second, by aggregating over time, we ignore the chronological order in which interactions between actors occurred. This neglect may change the interpretation of topological measures (Scholtes 2017).

Time in networks and temporal networks Historical relational data often include information about when an interaction occurred, such as the sending date of a letter. Including this temporal information in the network analysis, is essential in order to understand the dynamics that contribute to a historical context (Lemercier 2015).

Most approaches in HNR have addressed this problem by dividing up the observation period into smaller consecutive time windows. From the nodes which interacted in a time window an aggregated network was constructed for each window respectively. Topology measures were then applied to each aggregated network and compared over time.

Three issues are associated with this 'snapshot' approach: First, each snapshot aggregated network faces the same problems of topology uncertainty and time aggregation as the original aggregated network. Second, since the size of the time window affects network measures choosing the optimal one is crucial - however not straightforward (Budka et al. 2012; Uddin et al. 2017). Third, networks of individual time windows may not be comparable as they comprise different nodes. This incomparability may occur because some actors die and others are born throughout the observation period or because networks of different time windows differ in sample size (e.g. more historical records may exist for one temporal period compared to another).

Temporal networks provide a different class of network models that address these issues. A *temporal network* is a sequence of time-stamped edges each being defined as a tuple of two connected nodes and a discrete time-stamp at which the edge occurs (Scholtes 2017). Topological network measures have been successfully mapped to temporal networks (Scholtes 2019; Garas et al. 2014) and have been used to study a large variety of different types of systems: information exchange in ant colonies (Scholtes et al. 2016), passenger transfer in the London tube system (Garas et al. 2014), and clickstreams on Wikipedia revealing topic clusters (Scholtes 2017). To what extent temporal networks are applicable to letter correspondence data from the Reformation still has to be examined.

There are also three other established network models that take into account temporal information. The *relational event model* models the history of sender-receiver events by considering the probabilities of occurred and non-occurred but possible events (Butts 2008). The *temporal exponential random graph model* (tERGM) tests to what extent relations between nodes in the observed network as well as external relations determine changes in the observed network structure (Hanneke et al. 2010). The *stochastic actor-oriented model* (SAOM) assumes that the network topology changes because nodes, the actors, actively add or delete edges depending on specified formal rules (Snijders 1996; Snijders et al. 2010). As part of this doctoral thesis, it remains to be assessed to what extent each of these models is applicable to answer research questions related to the letter correspondences of reformers.

Multi-layer networks In real-world systems, components are usually connected by multiple types of relations. For example, reformers were not only connected via letter correspondences but also via kin- and professional relations, friendships, personal conversations, marriage, etc. Models that can incorporate this diversity are expected to represent the rich structure of the underlying system better than uni-relational models (Kivelä et al. 2014). *Multi-layer networks* represent a class of network models that incorporate multiple types of relations by projecting them to different network layers, respectively. Each layer holds the same nodes, which are connected in different ways depending on the type of relation. Several topological measures have been mapped from single-layer networks to multi-layer ones (Cozzo et al. 2015; Iacovacci et al. 2016; H. Zhang et al. 2017; Rahmede et al. 2018).

Given that a system includes lots of different types of relations it would be helpful to know how many layers we need in order to optimise the corresponding multi-layer network. Previous research has proposed some methods in this respect, such as quantum theory (De Domenico et al. 2015) and compressing layers with redundant information (De Bacco et al. 2017).

Moreover, we would also like to know which type of relation explains the underlying system best. Casiraghi (2017) addressed this network inference question with a *network regression model*. This model tests how well relational layers in the multi-layer network explain an interaction layer. With respect to the letter correspondence data of reformers, tested relational layers could represent the geographic distance between reformers or kin relations. The interaction layer represents the exchange of letters. To what extent multi-layer networks and the specific network regression model can be applied to the letter correspondence network of reformers, needs to be evaluated in this doctoral thesis.

Last, as data on all relation types may not be available for all node pairs, we have to deal with these inconsistencies systematically.

Network ensembles A *statistical network ensemble* (for simplicity from now only 'ensemble') is a collection of networks satisfying certain conditions. For example, all networks in the ensemble have the same average number of edges that link to nodes. One specific network that is part of the ensemble is called a *microstate* or *realisation of the ensemble*. The discussed network models so far all represented specific network realisations which face the issue of topology uncertainty: the topology might be influenced by random effects or by unobserved data and therefore may not capture mechanisms that drive the underlying real-world system.

Ensembles address the issue of topology uncertainty by encoding it in terms of probabilities. This framework allows us to apply inferential statistics in the following way: By fixing some network properties to create the ensemble (e.g. average number of edges that link to nodes) other network properties (e.g. clustering coefficient) are 'destroyed' since their patterns are randomised. We say that non-fixed network properties are *nullified*. When we now compare the ensemble to the observed network (the one we directly built from the data), we check how often a specific characteristic of our observed network (e.g. large clustering coefficient) occurs among the microstates of the ensemble. If the number of occurrences is above the statistical significance level, random effects were sufficient to generate the specific network characteristic from the observed network. We conclude that the tested network characteristic is not a meaningful property specific to the underlying system. In the other case, where the number of occurrences of the tested network characteristic is below the statistical significance level, random effects were not sufficient to generate the characteristic. We conclude that there must be some underlying mechanism specific to the system under study that generated the tested network characteristic. This latter case is the interesting one since it enables us to identify potential driving factors of the system.

The comparison between ensemble and observed network follows the same lines as hypothesis testing in frequentist inferential statistics mentioned in section **??** (What do we gain by applying inferential statistics to study the Reformation?). For example, we would like to test if a person is unusually tall compared to the height of her colleagues. Like the ensemble being a null-model that we compare to our observed network the height measures of the colleagues form the null-case to which we would like to compare our experimental case, the height of a specific person. If the height of that specific person is sufficiently different from the height of her colleagues (either the person is very short or tall), then we provided evidence that we cannot explain the difference in heights of the person and her colleagues by random effects. The term 'provided evidence for' is crucial. Since we deal with probabilities, we can never 'prove' a hypothesis but only indicate whether it is likely or unlike to be true.

The question now is how to construct an ensemble that is a suitable null-model? So which network properties should we fix and which ones nullify? Classical ensembles are the *Erdős-Rényi model* which fixes the number of nodes and edges (Erdos and Rényi 1960), as well as the *Configuration model* which adds the number of edges linking to nodes as additional fixed property (Molloy and Reed 1995).

A common characteristic of these ensembles is that they only hold edge-related properties fixed. This characteristic is problematic because many edges are unobserved (especially in historical data) and therefore observed ones do not capture all real-world connections, leading to a flawed null model (Nanumyan 2018). The *generalised hypergeometric ensemble* (gHypE) compensates for this uncertainty in edges by incorporating additional types of relations in the ensemble (Casiraghi et al. 2016). As in the configuration model, the gHypE starts with fixing the number of edges linking to nodes and assigns larger connection probabilities to nodes if their edge number is large. Going one step further, the researcher then formulates hypotheses of how other relations may affect the topology of the network. For example, in a communication network with additional relational data on friendships, a possible hypothesis may state that friends are three times more likely to exchange messages compared to strangers. The gHypE incorporates those hypotheses by adjusting the connection probabilities of nodes. If the resulting ensemble contains a sufficiently large number of microstates that match the observed network, then we provided evidence that our hypotheses represent underlying mechanisms that drive the system.

The *exponential random graph model* (ERGM) is another example of a network ensemble. It represents an alternative approach for explaining the network topology with additional relations between the nodes or processes in the network (e.g. reciprocity) (Robins et al. 2007). ERGMs are computationally expensive and therefore usually not suitable for networks with more than a couple of hundred nodes. Whether the benefits of ERGMs concerning the letter correspondence network outperform their computational costs has to be assessed within this doctoral thesis along with a more general evaluation of different network inference methods.

Network reconstruction Network measures are generally defined with respect to a completely observed global network (Wasserman and Faust 2009). Unfortunately, we only have access to an incomplete version of that global network since we deal with unobserved data (see section 2.1: Addressing peculiarities of the data).

Ad-hoc methods, such as treating unobserved edges as absent or dropping nodes with unobserved edge information, can produce flawed estimates of network measures (Almquist 2012). A more advanced approach is *network reconstruction*, the process of inferring a global network from an incomplete one which involves reconstructing missing nodes and edges.

Given the complexity of the problem, there is no one universal network reconstruction method that applies to several types of networks. Previous research has instead come up with individual methods each being tailored to one specific data set. The challenge of this doctoral thesis will be to review these existing methods, select and potentially modify the ones that apply to the letter correspondence network.

A large fraction of network reconstruction methods employs topological information. For instance, Fire et al. (2013) constructed several topological network measures for node pairs in a network and used supervised learning to reconstruct unobserved edges. This method provides a general framework which can be adapted to specific networks by choosing appropriate network measures as features. On the downside, the algorithm is computationally expensive and requires an observed global network from which to construct training and test sets. In the case of the letter correspondence network, the global network is not available meaning that we cannot evaluate this reconstruction method with our data of interest. As an alternative, the algorithm could be tested with synthetic data and then applied to the Reformation case.

Schall (2014) used *motifs*, local topological network patterns, to reconstruct the network. He counted the number of local network motifs two nodes are part of and from this computed their connection probability. Although the exact computation of edge probabilities remains obscure, this approach shows that sociologically-relevant motifs, like reciprocity, are prevalent in communication networks. Trying to maximise them in the letter correspondence network may be one approach to reconstruct the network.

Medo2018 reconstructed *bipartite* ecological networks which contain two types of nodes such as species being connected to locations. The authors then used the well-known fact that bipartite ecological networks display high nestedness (i.e. hierarchical structure) for reconstruction by adding those edges that would maximise nestedness. This approach is relevant for the Reformation case since the observed letter correspondence network can be interpreted as a bipartite network in the following way: Due to our main data sampling process, we received letter correspondences of seven principal reformers (see section 2.1: Dealing with fragmented data acquisition). We can map these seven correspondences to an ego network, respectively. An *ego network* is a star-network where one centre node (the ego), corresponding to one of the principal reformers from the sampling, is connected to all other nodes, the periphery. The peripheral nodes, however, are not connected among each other. If we construct one network out of the seven sampled letter editions, we receive a *superposition of ego networks*, meaning that the seven individual ego networks are connected via their centre nodes. This superposition of ego networks can then be interpreted as a bipartite network because egos and peripheral nodes correspond to two different types of nodes. To what extent the global letter correspondence network is expected to have a high degree of nestedness could then be analysed with specific topological network measures which have been shown to correlate with nestedness (Jonhson et al. 2013).

Since structural information is sparse in ego networks, topological network measures may not reconstruct the global network well. A second reconstruction approach, therefore, uses temporal information of the interactions in a network. For example, Tabourier et al. (2016) computed temporal features per node pair in a telecommunication network (e.g. do people make calls in the same time window). They then ranked these measures assigning higher edge probabilities to higher ranks. In the letter correspondence network, we could use temporal information in the form of sending dates. Analogously, spatial information may also be used to reconstruct the network. The sending and receiving locations of the letters could provide the data basis for this approach.

Rather than using the temporal information of edges Peixoto (2019) used an external dynamic process that acts on the network, like the spreading of disease. The temporal information of this process, such as the speed of spreading, was then used to reconstruct the global network with a non-parameteric Bayesian method. The method works best if the chosen external dynamic process matches the functional behaviour of the system, i.e. represent a plausible mechanism that acts on the network. Regarding the Reformation case, a letter correspondence network was probably more likely used to spread ideas than to spread diseases. Personal contacts would have rather transmitted diseases. Previous work has established functional forms for several dynamic processes such as the spread of diseases (Kermack and McKendrick 1927), of scientific ideas (Bettencourt et al. 2006), and of rumours (Nekovee et al. 2007), as well as reputation spillovers (Y. Zhang and Schweitzer 2019). We can test these functional forms on the letter correspondence network of reformers.

A third major approach employs information external to the network for its reconstruction. Additional relations between node pairs, such as kinship or employment relationship, can be used to infer the topology of the network. For instance, Wang et al. (2016) have used ERGMs to reconstruct unobserved edges and nodes in a friendship network of pupils. The pupils provided social and demographic characteristics as part of a survey which were used as predictors to infer the network structure. Together, these previous works suggest that promising network reconstruction methods already exist but have to be tailored to our Reformation case.

3.3 Our contribution

We will apply network models to the letter correspondence data of reformers and assess their suitability for studying social change during the Reformation. First, we will use networks to infer characteristics of individual reformers from their global letter correspondence structure alone. That is, without using biographical knowledge of individual reformers. The reformer-specific characteristics we focus on are religious ideologies and social roles. They exemplify social change during the Reformation by the shift from uni- to multi-denominations and social differentiation, respectively.

Second, we will use networks to test hypotheses on how social relations affected the letter correspondence during the Reformation. Given that letters were the primary means of communication in the 16th century (besides personal conversations), they were likely to contribute to the spread of social change. Thus, examining the factors that shaped this communication is an essential contribution to the understanding of social change during the 16th century.

Third, we will explore the role of network methods to solve the methodological issues of unobserved data. We will quantify the bias introduced in the results by unobserved data, try to reconstruct the global network from the observed one and from this infer in which ways data collection of Reformation letters is biased. The generated insights will be of use for the Digital Humanities and Computational Social Science.

4 Research questions

4.1 Inner-protestant conflicts

Ingroup favouritism is a behavioural pattern where an actor favours members of her own ingroup over members of her outgroup (Taylor and Doria 1981). It manifests in the evaluation of others, allocation of resources, and many other ways of behaviour, which are linked to group conflict and the formation of prejudice. Examples of ingroup favouritism occur throughout history and in all aspects of social life, including rivalries between football clubs, racism, and contemptuousness of other job sectors.

The Reformation was no exception in this regard. Different protestant denominations formed which did not only fight against the Catholic Church but also competed among each other for the 'right' implementation of Christian faith. The most prominent denominations driving these inner-protestant conflicts were the Lutherans and the Reformed. Exemplary disagreements included the doctrine of predestination arguing whether God grants salvation to everyone (Lutherans) or only to some chosen people (Reformed) and the Eucharist dispute where the presence of Christ is real (Lutherans) or symbolic (Reformed).

This doctoral thesis will examine to what extent the inner-protestant conflicts manifest in the letter correspondence network of reformers. The corresponding research question reads:

RQ 1a: Inner-protestant conflicts

How can we identify the extent of inner-protestant conflicts among reformers from their letter correspondence network?

Previous research has provided evidence for a strong positive relation between the amount of communication and ingroup favouritism. This relation was shown for real-world project teams of co-located and virtual team members (Webster and Wong 2008), as well as in computational models where agents played social dilemmas (Nakamura and Masuda 2012). The strong association remained even for task-irrelevant but personal communication (Buchan et al. 2006).

Against this background, we would like to apply *community detection* in the communication network of reformers as our methodological approach to address RQ 1a. A *community* is a group of nodes that is more interconnected than other groups of nodes. In the letter correspondence network of reformers, the level of interconnectedness corresponds to the amount of communication. Specifically, our envisioned approach includes the following steps.

Envisioned approach

Step 1 Define requirements for community detection algorithm, based on characteristics of observed letter correspondence network.

Step 2 Apply suitable community detection algorithms to network and compare their outcomes.

Step 3 Validate results by consulting historians (e.g. check spot-test sample).

This approach is based on two main assumptions:

Assumptions

A 1 Protestant denominations are the relevant concept of inter-group distinctions, so that supporters of the same denomination form an ingroup.

A 2 Increased communication between group members is a manifestation of ingroup favouritism.

By applying the approach above, we test the following null hypothesis H_0 and formulate the alternative hypothesis H_1:

Hypotheses

H_0 The amount of interconnectedness between reformers does not indicate which protestant denominations reformers support.

H_1 The more interconnected groups of nodes are, the more likely the corresponding reformers support the same protestant denomination.

We are aware that our envisioned approach is not free from potential problems. The first concerns the relationship between the detected communities and the ground truth (see assumption *A 1* above). In real-world networks, we neither know the correct partition nor the data generating process. This implies that a ground truth on communities does not exist (Peel et al. 2017). We instead usually use observed node attributes as a proxy for the unknown ground truth and evaluate the community detection algorithm by how well its resulting communities match the node attributes. However, it remains unclear whether the chosen node attributes are (1) relevant for the structure of the network and whether (2) the detected communities and the node attributes capture the same aspects of the network structure (Peel et al. 2017).

With respect to the Reformation, we know that many different conflicts existed, such as Protestants vs Catholics, radical vs conservative reformers, theologians vs lawyers, and pro-peasants vs pro-princes. Thus, the inner-protestant denominations are just one of many possibilities of what network communities could represent. In order to address this problem, we could generate node attributes for the major inter-group conflicts of the Reformation mentioned above and test cases (1) and (2) with the proposed entropy measures of Peel et al. (2017). This aproach would, however, require an exact match between reformer and label of his conflict group, since the entropy measures are based on interval data. Considering that no such systematic data set exists, establishing it for about 2,500 reformers requires a lot of manual work and expert knowledge.

The second problem is that reformers could be part of many different groups and support them to different extents. This ambiguity is not captured by network communities which assume clearly defined community boundaries and assign each node to one community only. As a result, the validation procedure will not be systematic since each historian evaluates the ambiguity in the observed node attributes differently.

The third problem addresses the unsystematic character of spot test in our planned validation procedure. Since humans will conduct our validation, who have limited time and cognitive capacities, we use spot tests rather than evaluating all 2,500 reformers. Since we choose the nodes that are part of a spot test at random we can neither easily reproduce the validation results nor can we exhaustively assess the community detection procedure.

Given the nature of the Reformation as a transformative movement, we know that the protestant denominations and other groups were no static entities but developed over time. For example, whereas the Lutherans and Reformed became established groups already in the late 1510s Calvinism did not appear before the late 1530s just because Calvin was much younger than Luther and Bullinger. Moreover, as Calvin spent many years in Strasbourg he was heavily influenced by Lutheran ideas before founding his own protestant denomination. For example, he signed the Augsburg Confession, which reflected the wording of the Wittenberg Concord although Calvin was never Lutheran according to the definition of Lutheranism in the Formula of Concord.

In order to capture these dynamics, we would like to examine the formation and dissolution of protestant denominations over time. The corresponding research question reads:

RQ 1b: Inner-protestant conflicts

How can we extract the temporal formation of inner-protestant conflicts among reformers from their letter correspondence network?

Our approach relies on community detection in the letter correspondence network. In addition to the problems associated with RQ 1a we will also have to examine how the choice of the sub-periods affects the detected communities and to what extent sub-networks are comparable across sub-periods.

Envisioned approach

Step 1 Divide observation period into sub-periods and construct aggregated snapshot for each subperiod.

Step 2 Apply steps from RQ 1a to networks across all sub-periods.

4.2 Social differentiation

Social differentiation is a process in society, where people increasingly become more specialised in the tasks and roles they fulfil (Ritzer and Stepnisky 2017). During the Reformation, social differentiation was very prominent. It lead to specialised professional networks on astronomy, botany, antiquarianism, and theology (Miert et al. 2019). Although most of the erudites were both scholar and scientist, theologian and philosopher, they focused on one subject more intensely.

Since we do not consider the content of the letters in our analyses, we cannot examine the differentiation on a professional level during the Reformation. Instead, we would like to see to what extent social roles are subject to social differentiation. *Social roles* are a set of behaviours that are expected of someone who holds a particular status. Examples include leader, servant, student, adviser, or misfit. We aim to extract social roles of reformers from the topology of the letter correspondence network and evaluate how they change over time. We propose the following research question:

RQ 2: Social differentiation

How can we track the extent of social differentiation among reformers in their letter correspondence network over time?

We plan to measure social roles with topological network measures such as centrality as suggested by the RolX algorithm for role detection (Henderson et al. 2012). Specifically, we will apply a sample of carefully selected and engineered measures on the network in order to receive a measured value for each node and network measure, respectively. These measures are then projected into a lower dimensional space which defines the social roles. That is, several original measures project onto the same social role but to different extents, and similarly, each node can project onto several social roles.

Envisioned approach

Step 1 Divide observation period into sub-periods and construct aggregated snapshot for each sub-period.

Step 2 Define real-world social roles of interest.

Step 3 Define selection criteria for topological network measures that capture the chosen real-world social roles.

Step 4 Construct/choose topological network measures based on selection criteria.

Step 5 Apply RolX algorithm to each sub-network

This approach is based on three main assumptions:

Assumptions

A 1 Social differentiation also affects social roles (and not only professions).

A 2 Social roles are encoded in the topology of the letter correspondence network.

A 3 Institutional roles are excluded from the analysis (e.g. a beggar and a prince having the same position in two identical networks would have the same social role).

By applying the approach above, we test the following null hypothesis H_0 and formulate the alternative hypotheses H_1 and H_2:

Hypotheses

H_0 As time increases, the spectrum of roles per person and the spectrum of weights per role do not change.

H_1 As time increases the number of roles a person is associated with decreases.

H_2 As time increases the allocation of weights becomes more heterogeneous over roles (i.e. only a few roles will have large weights)

Considering the envisioned approach above we face several problems. First, translating real-world social roles into topological network measures may not be straightforward. Second, since unobserved data heavily influence the network topology, applying role detection on the observed network may lead to flawed results. We can better use the reconstructed network from RQ 5b for this task. Third, we have to examine to what extent sub-networks of the different sub-periods can be compared to each other and consequently, how their role spectra relate to each other. This aspect is relevant for examining the temporal development of these spectra. It is important to note that the issue of unsystematic validation associated with RQs 1a and 1b does not apply to RQ 2 since we are not interested in the specific match of a reformer to his social role. Instead, we look at changes in the size of the spectrum of social roles.

4.3 Confessional formation

Confessional formation describes the adoption and institutionalisation of Protestantism, especially how church and state cooperate in this respect to discipline their subjects (Schindling 1996). Of specific interest in this respect are the territories of the Holy Roman Empire which were autonomous regions governed by princes and other noblemen. The territory rulers had the full power of control over their subjects and, therefore, also determined the 'official' religion of their subjects. This ruler-based choice of religion became HRE law at the Augsburg Interim in 1555 but had been already executed unofficially earlier (Burkhardt 2002).

Why did some territories adopt Protestantism, whereas others remained catholic? In his theory on the process of confessional formation in protestant territories, Stievermann (1996) identifies seven main causal factors: (1) Character of the ruler, (2) character of subjects, (3) resistance of catholic forces from within the territory, (4) power of neighbouring territories, (5) dynastic relationship with other territories, (6) proximity to Emperor, (7) transfer of 'top theologians' who acted as 'consultants' for territory rulers. Other theories with different factors may exist, too. We are now interested in establishing quantitative measure of these factors. We state the corresponding research question:

RQ 3a: Confessional formation

How can we quantify the factors that have affected the adoption of Protestantism during the Reformation according to descriptive theories?

Envisioned approach

Step 1 Select factors that are thought to have influenced the adoption of Protestantism by theorists (e.g. Dieter Stiervermann).

Step 2 Construct a territory-specific data set (e.g. crawl territory infoboxes on Wikipedia).

Step 3 Build measures of the theoretical concepts using the constructed territory data set.

Step 4 Validate the constructed measures.

The following measures could potentially serve as quantitative counterparts of Stievermann (1996)'s factors: (3) resistance of catholic forces from within the territory measured by the number of monasteries in this territory, (4) power of neighbouring territories measures by their surface area, (5) proximity to Emperor measured by title of the ruler (e.g. an electoral prince being closest to the Emperor, a duke being furthest away), (7) transfer of 'top theologians' who acted as 'consultants' for territory ruler measured by the amount of inflow of top-theologians who would be picked manually (e.g. 20 most active letter writers). Factors (1) and (2) refer to individual attributes of people and would require an enormous amount of manual work to be constructed. They are therefore excluded from the analysis for now. Factor (5) requires an additional marriage network of the HRE. Since the collection of the relevant data is very time-intensive, this factor will also be excluded from the analysis. More refined or additional measures can of course be developed during the main analysis.

This approach is based on one main assumption:

Assumptions

A 1 Theoretical causal factors for confessional formation in territories can be approximated by quantitative measures.

Given that we answer RQ 3a, i.e. successfully translated the theoretical causal factors into quantitative measures, we now would like to test these measures in a statistical model. We propose the following research question for this purpose:

RQ 3b: Confessional formation

How can we quantify the effect of theorised factors on the adoption of Protestantism by territories of the Holy Roman Empire?

In a first step, we would like to predict whether territories adopt Protestantism or remain catholic. For this purpose, we could use a logistic regression. In a second step, we would like to infer relevant factors for the adoption of Protestantism statistically. In order to apply this inference, we can still use logistic regression but have to check stricter assumptions on the random errors and correct for multiple hypotheses testing.

The cases so far dealt with correlations, i.e. the predictor are associated with the adoption of Protestantism in the territories but no causal relationship is established. Take the character of the ruler as an example of a predictor. The territory could become protestant because the ruler is especially open-minded or the ruler could become open-minded because the territory becomes protestant. Since qualitative theories on why territories adopt Protestantism deal with causal factors, we would also like to test our constructed measures for causality.

In theory, testing for causal relationships requires two parallel universes which are identical except for a process or an event that is supposed to cause some change. If this change occurs in one universe but not in the other, we can conclude that the process or event was indeed causal since the universes were identical otherwise. As parallel universes do not exist in the real world, we approximate this theoretical setting by randomised experiments, such as in medical trials which test the effect of drugs. However, since our letter correspondences and territory data are observational data, we cannot randomly assign reformers, territories, or other historical entities of interest to an experimental and a control group and check whether the groups' reactions to treatments (e.g. laws, wars, famines) differ.

We, therefore, have to turn to other models to test for causality under observational data. Angrist and Pischke (2009) examined three established inferential models and defined conditions under which these models can be interpreted as causal: Linear regression, instrumental variables method, and differences-in-differences methods. Our aim in the third step is to scrutinise these models and, if suitable, apply them to our data.

Envisioned approach

Step 1 Test assumptions of models in prediction setting (e.g. regression models).

Step 2 Build a suitable statistical model to predict the adoption of Protestantism in the territories from the measured factors (e.g. logistic regression).

Step 3 Test assumptions of models in inference setting (e.g. for regression check distribution of random errors).

Step 4 Select relevant predictors (correct for multiple hypotheses testing).

Step 5 Perform separate model assessment with the test set.

Step 6 Think of inference questions beyond model selection and apply them.

Step 7 Examine causal models and the conditions under which they apply.

Step 8 Potentially apply the causal model to data.

Depending on the statistical model, we have to meet different assumptions concerning the distribution and generation of data. These assumptions will be checked and further discussed once a suitable model is selected. By applying the approach above, we test the following null hypothesis H_0. Since qualitative theories on the adoption of Protestantism do not provide any ranking of factors (which one is more responsible for the adoption of Protestantism) we only formulate a very general alternative hypothesis H_1:

Hypotheses

H_0 All predictors are zero and therefore do not predict the adoption of Protestantism.

H_1 At least one predictor is non-zero.

The largest problem of this approach (RQ 3a and 3b) is the data generation. Constructing the predictors and the response of whether a territory adopted Protestantism require the generation of a new, territory-specific data set. We have to identify relevant territories (there are more than 600) and have to collect their relevant characteristics. One of our pilot studies tried to speed up this task by crawling Wikipedia for territory information. Although this seemed to be a promising option, much manual work will likely be involved in this process as Wikipedia does not list all territories. Also, we will probably have to deal with unobserved data as many characteristics will not be available for all territories.

Moreover, the validity of the constructed measures may be a potential problem and also finding a systematic way of validating these measures.

4.4 Mobility

The Reformation was a period of high individual mobility. Students travelled between universities and delivered letters of recommendation from their professors. 'Top' theologians moved between residences of territory rulers to consult them on the implementation of reformist ideas. Scholars met at various places in the Holy Roman Empire to dispute over protestant ideas. Expelled reformers moved to new territories where their ideas were supported. New economic opportunities (e.g. banks) increased the travel and interaction of merchants (Burkhardt 2002; Kaufmann 2017; Strohm 2017). This mobility increased the spread of ideas and goods in Europe.

Due to the autocratic rule of the aristocracy in the 16th century, subjects heavily depended on the will of their territory ruler (Stievermann 1996; Strohm 2017). Thus, their personal decisions were probably constrained much more by political changes than that of European citizens today. Individual mobility represents an example of a personal decision, as the person has to decide whether and where to move. We are interested in examining whether political changes influenced individual mobility in the 16th century. The corresponding research question reads:

RQ 4: Mobility

How can we quantify the effect of political changes on the movement of reformers between territories in 16th century Europe?

A specific political change in the 16th century was the Augsburg Interim (1555) where the Peace of Augsburg was signed. This new law allowed territory rulers to choose the religious denomination of their subjects. As a consequence, different territories supported different denominations and subjects could move between territories to settle where their belief was supported officially. This new law was a major change since beforehand territory rulers were tied to the Catholic Church and expected to accept the catholic belief, also for their subjects, by default.

Another decisive political change was the Schmalkaldic War (1547), where pro-reformist princes fought against pro-catholic imperial troops for their religious freedom. Although the princes were defeated, the war helped them to become further independent from the Emperor and the Catholic Church and also signal this break to their subjects.

Since both, the Peace of Augsburg and the Schmalkaldic War, provided incentives for subjects to move to territories where their individual belief was supported, we think that these events provide good candidates to test their effect on mobility. We, therefore, plan to conduct the following analysis with one or both of these events and may include other political changes if necessary. Note, that the effect of the Peace of Augsburg has to be examined together with the territory's individual decision to switch from Catholicism to Protestantism or to remain Catholic. Since this decision is a direct consequence of the Peace of Augsburg, we can relate this decision to mobility.

We quantify mobility by the in- and outflow of people per territory. The sequence of reformers' sending locations from the letter correspondence data approximates reformers' whereabouts. These locations are then linked to territories with the territory-specific data set constructed for RQs 3a and 3b. In order to check whether political events affect the flows, we first compare the amount of flow before the political change (unaffected) with the one after the change (affected). Along the same lines, we compare the flows of territories that remained catholic (unaffected) to the ones that switched to Protestantism (affected). If the affected and the unaffected groups differ in flows, then we cannot rule out the possibility that the political change had an effect. We cannot absolutely claim this effect, since the affected and unaffected groups may differ on other characteristics (e.g. wealth, amount of wars fought). If these other factors are not randomised across the unaffected and affected groups, we may associate *them* with the difference between the unaffected and affected group rather than the political change we are trying to test. For the same reason, we cannot make any causal claims at this stage (see section 4.3: necessity for randomised control experiments for causal inference).

In order to test whether a political change causes changes in the amount of mobility we plan to use the following approach. In case of the Peace of Augsburg which made some territories switch to Protestantism, we first gather all factors that may be responsible for why a territory switched to Protestantism. These factors were examined in RQs 3a and 3b and are based on qualitative theories of confessional formation (Stievermann 1996). Second, we build a model predicting which territories should switch to Protestantism (e.g. regression or decision tree). This model returns a probability for each territory, indicating how likely this territory is to adopt Protestantism. Third, we apply propensity matching, meaning that we group territories with similar probabilities to switch to Protestantism together. Although the probabilities are similar for each of these groups, territories differ in their real-world decision. For example, considering one such group of ten territories, all having a probability of 0.6 to switch to Protestantism. On average, six of those territories have adopted Protestantism in the real-world, and four have remained Catholic. Fourth, we now compare territories that became Protestant to the ones that remained Catholic for each probability group. Due to the model and the propensity matching the Protestant and Catholic territories are identical in *all* aspects except for their real-world decision to switch. If these Protestant and Catholic territories differ in their in- and outflows we can conclude that this difference *must* be due to the difference in supported denominations, which is a direct consequence of the political change: the Peace of Augsburg.

Envisioned approach

▶ Correlation without control factors

Step 1 Compare sum of in-and outflows to territories before and after a political change (e.g. 1555 for Peace of Augsburg).
Compare number of reformers who moved before 1555 (a) to the number of reformers who moved after 1555 (b). If $b \neq a$ it cannot be ruled out that Peace of Augsburg affected mobility.

Step 2 Compare in- and outflows of territories in the years after they switched to Protestantism to the in- and outflows of places that remained catholic.
For all territories that switched from Catholicism to Protestantism compute the sum of in- and outflows of reformers t years after the switch (b). Do the same for territories that remained catholic (a) (since there is no switch date use aggregated number of people going to that place). Check if $b \neq a$, i.e. flows of switched and non-switched places differ.

Step 3 Compare in- and outflows of places over time and check for an increase in flows once place became protestant.
Move overlapping sliding time window over observation period. For each window and each territory calculate the number of people going to that place. Align time windows of territories so that window where the real-world switch from Catholicism to Protestantism occurred match. Aggregate the number of people going to a territory over all aligned time windows. Check for a change in in- and outflows at the time where the territory switched from Protestantism to Catholicism

▶ Causation with control factors

Step 4 Select possible models to predict adoption of Protestantism per territory from territory-based predictors (see RQ 3a).

Step 5 Check if data meet model assumptions.

Step 6 Build model.

Step 7 Apply propensity matching to select those places that have equal probabilities of switching to Protestantism.

Step 8 If territories with the same probabilities differ in their real-world decision, their differences in in- and outflows are due to real-world decision.

This approach is based on one assumption:

Assumptions

A 1 Sending and receiving places of letters approximate whereabouts of reformers.

By applying the approach above, we test the following null hypothesis H_0 and the alternative hypotheses H_1 and H_2.

Hypotheses

H_0 In- and outflows of reformers to and from territories do not differ before and after a political change.

H_1 In- and outflow of reformers to and from territories is larger after 1555 (Peace of Augsburg) than before.

H_2 Territories that switched to Protestantism have larger in- and outflows of reformers than territories that stayed Catholic.

As with RQs 3a and 3b it will be difficult to construct the territory-specific data set. Furthermore, making strong causal claims will not be possible since this requires to include *all* possible control factors that influence the switch from Catholicism to Protestantism of a territory. Such an exhaustive set of predictors cannot be constructed, which has to be taken into account in the interpretation of the results.

4.5 Unobserved data

One peculiarity of our letter correspondence data set is that we have to deal with unobserved data, as explained in section 2.1 (Addressing peculiarities of the data). We neither have access to all letters having been written during the Reformation nor to all their senders and receivers. As a consequence, our reconstructed letter correspondence network is *incomplete* relative to the global real-world letter correspondence during the Reformation.

Analysing only observed data is common practice in inferential statistics. As scientists typically do not have access to the full population of interest, they take a random sample of it and infer insights about the population from the sample. For instance, consider predicting the outcome of elections. Before an election, we cannot ask all eligible voters about their planned choice. Instead, polls randomly select people among eligible voters and ask them about their planned choice. This inference works because the sample is representative of the population. As discussed in section 2.1 (Addressing peculiarities of the data) this is not the case for our observational data due to sampling bias.

As a result, our reconstructed incomplete letter correspondence network is a superposition of ego networks. An *ego network* is a star-network where one node, the centre, is connected to all other nodes, the periphery, where the latter are not connected among each other. In a superposition of these ego networks, the centres are interconnected. Even though we know that the superposition of ego networks yields a different network than a global one, we still have to quantify the effect of this difference on statistical measures. If the effect is small, we may neglect the difference between the incomplete and the global network and use the incomplete for all analyses. In order to address this matter, we formulate the following research question:

RQ 5a: Unobserved data

How does the superposition of ego networks affect network measures?

To simplify matters, we assume for the moment that the global network consists of the same nodes as the corresponding incomplete network. That is, we neglect the fact that we also deal will unobserved nodes and only focus on unobserved edges. This restriction is necessary in order to confine the pool of possible global networks corresponding to an incomplete one to a finite size.

Envisioned approach

Step 1 Gather topological characteristics of a communication network.

Step 2 Use these characteristics to construct an artificial global network.

Step 3 Alternatively, use a real-world global communication network (e.g. enron)

Step 4 From global network extract some ego nodes and their neighbours and super-impose these ego networks.

Step 5 Add links iteratively to the superposition of ego networks until the complete network is reconstructed.

Step 6 In each iteration, compute network measures and track their development over time.

This approach is based on two main assumptions:

Assumptions

A 1 The incomplete and global network differ in terms of edges but comprise the same nodes.

A 2 Topological characteristics of global modern communication networks approximate the ones of the global letter correspondence network of reformers.

Assuming that the differences in statistical measures of the incomplete and global networks are non-negligible (RQ 5a) and given the fact that we cannot change the sampling procedure of observational data we have to find a way of reconstructing the global letter correspondence network if we would like to infer characteristics about the Reformation. The corresponding research question reads:

RQ 5b: Unobserved data

How can we infer the global network from the superposition of ego networks of reformers?

A global network is beneficial because it (1) provides a more balanced view on the role of allegedly important and unimportant actors during the Reformation, (2) provides a direction for researchers where to look for unobserved letters, (3) increases confidence in statistical models to test theories.

Since we only consider unobserved edges our network reconstruction problem translates to an edge reconstruction problem. We would like to test and compare different approaches for network reconstruction, in line with the ones presented in section 3.2 (Network reconstruction). In the topological approach, we plan to extract characteristic topological features from modern global communication networks (e.g. enron, see RQ 5a) and add edges to the incomplete letter correspondence network that maximise those features. This approach assumes that modern and historical communication networks share topological characteristics. Thus, insights from the modern globally observed network can be applied to the incomplete historical one. For example, modern communication networks are characterised by a large degree of *triadic closure*: if two people A and B communicate with another person C, respectively, then A and B are very likely to communicate with each other, too. On the one hand, this approach is overly-simplistic as it directly reasons from modern to historical network features and does not take into account specific subtleties of the letters correspondence network. On the other hand, it is relatively cheap because it does not require generating new data features.

Second, we plan to employ temporal information as in Peixoto (2019) non-parametric Bayesian approach for network reconstruction. We will choose an existing model describing the dynamics of a functional behaviour that is likely to have acted on the letter correspondence network, such as the spread of ideas. The challenge will be to incorporate these dynamics into the existing reconstruction model. On the upside, a full implementation of Peixoto (2019)'s reconstruction approach is available online such that only a small part has to be coded from scratch.

Third, we would like to use network inference methods for reconstruction. As explained in section 3.2 (Network ensembles, Network reconstruction) additional relations between the nodes can be used for this purpose. These relations can be *endogenous*, i.e. derive from the topology of the incomplete network itself or be *exogenous*, i.e. derive from external relationships between the nodes. In the letter correspondence network, reciprocity and triadic closure are examples for endogenous relations whereas kinship and geographic distance are examples of exogenous relations. Since exogenous relations are very cumbersome to construct for the letter correspondence network, their selection has to be carefully motivated. Based on these additional relations, network inference models quantify the probabilities of each node pair being connected. Furthermore, these models provide estimates on how important each relation is for explaining the to-be-reconstructed network.

The use of ERGMs for this reconstruction approach has already yielded promising results for small networks (Wang et al. 2016). We have to investigate whether the high computational costs of ERGMs outweigh their benefits in terms of network reconstruction in larger networks, such as our network of letter correspondences. If they do not, an alternative approach is needed, such as the network regression (see section 3.2: Multi-layer networks). It is based on the hypergeometric network ensemble which is analytically tractable and therefore computationally much less expensive than ERGMs (Casiraghi et al. 2016). Since the network regression is a rather young model, its suitability for network reconstruction has to be examined in a more explorative sense than for the more established ERGM.

Envisioned approach

- General

Step 1 Conduct thorough literature review on edge reconstruction methods. Define criteria for methods that are applicable to the letter correspondence network.

- Topological approach

Step 2 Select characteristic topological features of modern communication networks.

Step 3 Implement an edge reconstrcution mechnism that maximises these selected features in the letter correspondence network.

- ERGM and Network regression

Step 4 Select factors that are thought to influence the letter correspondence between reformers.

Step 5 Build measures of these concepts.

Step 6 Conduct ERGM-based reconstruction based on existing implementations (e.g. Wang et al. 2016)

Step 7 Conduct network regression to reconstruct missing edges.

- Bayesian approach

Step 8 Evaluate concept and implementation of Bayesian approach.

Step 9 Select meaningful network dynamics (e.g. information spreading) and choose appropriate model representing these dynamics.

Step 10 Use dynamics to implement Bayesian approach.

Step 11 Thoroughly evaluate and compare tested approaches.

This approach is based on assumption A2 from RQ 5a.

Assumptions

A 1 Topological characteristics of global modern communication networks approximate the ones of the global letter correspondence network of reformers.

So far, we ran a promising pilot study with three predictors in the network regression approach. For the topological approach, we conducted a screening of promising topological features. This screening still requires some final checks. The remaining approaches, ERGM and Bayesian, require further conceptual investigations. We expect the most time-consuming and challenging tasks to be the gathering of data on relevant social relations, the construction of adequate measures, and their validation for the network regression and the ERGM-approach.

5 Schedule

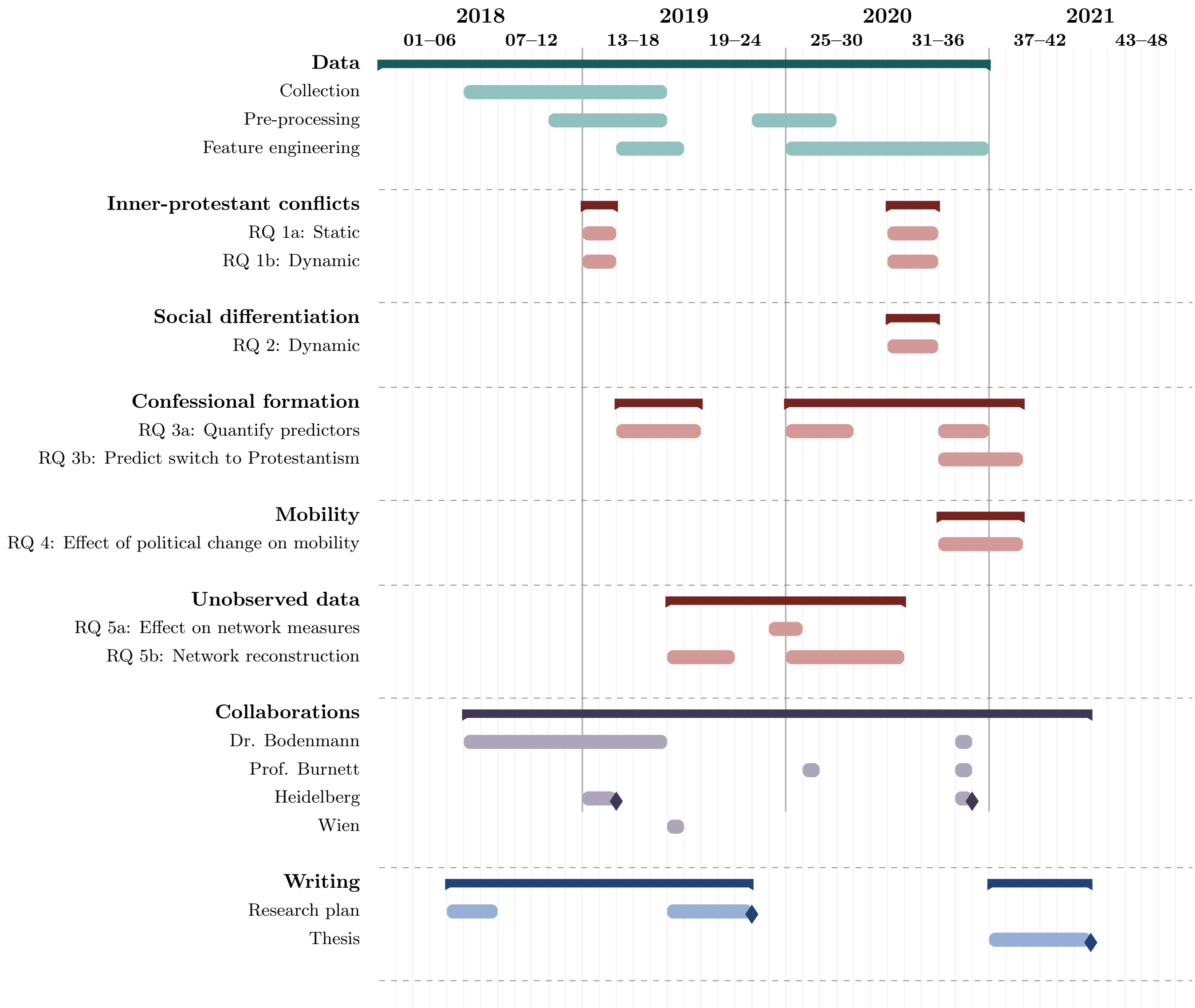

Figure 1: Timing of addressing research questions and other building blocks of PhD project

Figure 1 shows the preliminary schedule to address the research questions and eventually write-up the doctoral thesis. Dark-coloured bars refer to periods in which general topics of this thesis will be addressed, respectively. Light-coloured bars refer to the periods that are allocated to address specific research questions.

Based on the insights gained during the exploration phase, i.e. January 2018 until November 2019, the next step will be to refine data pre-processing and collection. The first focus will be on integrating all loose data sets into one data base. The second focus will be on generating a territory-specific data set and new data features. This will answer RQ 3a and provide the necessary predictors for RQ 3b, 4, and 5b.

In parallel, we will start to address RQ 5a. Since this research question only depends on synthetic data and the enron data set, we do not need to finish the pre-processing and feature engineering steps beforehand. Moreover, the required methodology for RQ 5a is clearly defined and straightforward. We, therefore, expect this research question to be answered quickly.

Once RQ 5a is answered and the data-related tasks are sufficiently advanced, we will intensely focus on RQs 5b at a stretch. Answering RQ 5b as early as possible is necessary, since we may require the global network to address topological RQs 1a, 1b and 2. These three research questions will therefore be addressed over the summer in 2020. In order to answer RQ 5b, we will start with testing topological and temporal methods, since these only require a well-pre-processed data set but no additional data features. At a later stage, we will focus on feature-based methods such as network regression and ERGMs.

Since RQs 1a, 1b and 2 all use topological network measures, they are best answered together. Validating the results is the largest challenge associated with these research questions. We, therefore, aim to discuss preliminary results with historians at the workshop on historical letter analysis taking place in Heidelberg in September 2020. In order to have fresh results ready at that time, we allocate the preceding summer months to these research questions.

Subsequently, we will address RQ 3b and 4 in the autumn and winter of 2020 and 2021.Since these two research questions rely most heavily on engineered data features, we want to allow sufficient time for these data features to be constructed before addressing the respective research questions. Moreover, both research questions address problems of prediction and inference with potential causal interpretations. Thus, we may apply similar models to both research questions and can use insights gained on one research question for the other one. Last, input from historians is only required to validate the quantitative measures for the predictors but not to validate the final results of the inferential models. We, therefore, deliberately address RQs 3b and 4 after the workshop in Heidelberg for methodological reasons, although the results would be of interest to historians, too.

The four milestones of this PhD project are indicated by diamonds in figure 1. They refer to (1) the scientific meeting in Heidelberg, where we set up a closer collaboration with the theological research group (January 2019), (2) the submission of the research plan (October 2019) which formulates research questions and plans the methodology to be used, (3) the historical letter workshop in Heidelberg (September 2020) which provides an opportunity to test our results in the Digital Humanities community and eventually the (4) defense of the thesis (early summer 2021).

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