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Searching for the Dutch Corner in the Republic of Letters: Network Science and Wittgenstein's Family Resemblance

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This article has a twofold contribution. First, it offers a new way to consider communities that are conceptually and analytically difficult to define. This method has been based on the philosopher Ludwig Wittgenstein's notion of "family resemblance" applied here through a novel quantitative process, using the online knowledge base Wikidata and bespoke visualisations to identify communities in large epistolary datasets. A bipartite analysis based on shared characteristics, rather than evidenced personal connections, makes it possible to map a large community of individuals, which reveals clusters of similarity and shared features. In a break from most existing applications of historical community detection, a different approach is used here, using a network object known as a multigraph, which allows characteristics to be viewed both as individual attributes and as parts of overlapping sets.

Second, this article describes an application of this method to uncover a community that is often discussed but notoriously difficult to define and analyse: the Dutch Republic of Letters. This loose, early modern sub-community included members from different denominations, professions, origins, and affiliations but has been recognised qualitatively as a body of prolific and intellectually bonded individuals, with links within and beyond the United Provinces. In applying this method, we create a truer picture of how communities such as these operated and cohered, while avoiding reductive criteria for inclusion of such individuals. The uncovering of this particular Dutch community is a clear demonstration of this method in action and therefore offers a successful alternative to other community detection methods.

Introduction

This article presents a novel means of conceptualising and analysing communities, in our example through correspondence networks of the seventeenth century within the Dutch Republic. Many real-world networks—be they social, biological, computer, or others—are found to naturally form sub-communities or "modules."[1] These are nonetheless often difficult to find or define, since inclusion and exclusion criteria can be difficult to establish outside the dynamics of the network itself. Intellectual and epistolary networks are no different, since membership of a community can be determined by numerous mutable factors. As Karen E. Spierling and Michael J. Halvorson write in *Defining Community in Early Modern Europe*, "the meanings and applications of this complex word [community] have been approached in many different ways by historians, sociologists, anthropologists, philosophers, and literary scholars. The danger lies not in trying to analyse community dynamics but in attempting to impose too great a clarity, simplicity, or transparency on the operations of any particular community" (1). Though the defining of a community or communities can be helpful in understanding them—and necessary for their study—any definition also poses risks of exclusion, simplification, and arbitrariness. Here, we provide a method that considers both the conceptual and the computational challenges of community.

This article consists of three parts. The first part introduces different current methods for locating communities, in particular communities of people in historical data, and these methods' significant limitations. We are attempting to overcome some of these with our "family resemblance" concept, as coined by Ludwig Wittgenstein, which is used as the basis for a new computational approach. It is sensitive to the conditions of the network as a whole while still offering substantive findings about how the community structured itself. The second part of this article introduces a case study of a community, a part of the Republic of Letters that was centred in the Dutch Republic, which is difficult to define and does not have a single shared characteristic between its members. The data used for this case study comes from *Early Modern Letters Online* (hereafter EMLO). The third part demonstrates the application of the method and the experiment and shows how it can accurately be applied to big-scale data in order to suggest communities with fluid boundaries and definitions. This article offers a network analysis approach that can be complementary to more traditional modes of considering community, thereby shedding light on those elusive clusters of connection that are otherwise difficult to grasp.

[1] Community detection algorithms assess how well a given set of groups describe the network using a value called "modularity," which is the number of links that fall within groups minus the number in an equivalent network with the links set at random (see Newman 8577–82).

Part 1

Methods for Locating Communities

In network analysis, a community is loosely defined as a sub-group within a network which has closer ties between its members than it does to those outside (Newman 8577–82). Various methods within the field of network analysis allow us to represent this kind of network mathematically (Barabási; Albert and Barabási). The data in EMLO used here consists of a collection of letters, which contains the letters themselves but also data about the authors and recipients. One natural mode of analysis when faced with a large dataset with people and letters is to consider it as a social network of sorts, with ties between people evidenced by the letters they sent and received.[2] If we consider the epistolary connections as evidence of a social network, detection of groups within it has some obvious uses, allowing us, for example, to track community changes over time or to understand the roles of sub-communities or central players (Newman 8577–82).

Several computational methods are available to define communities, but it is worth considering the particular limitations of each in order to clear the ground for our chosen approach.[3] A specific concern is that many methods are not satisfactory for communities that cannot be captured by the presence of a single unifying characteristic. The examples below are centred around the use of letters as examples of connection since our method, too, takes this as a starting point.

One option—more closely replicating the work of some traditional scholarship—is to start with a key individual or list of individuals and extract their "ego network," or the individual's immediate contacts and all the ties between their contacts. The strongest ties within such a group may reveal relevant communities. Despite its appealing clarity, this approach has several problems: anyone without direct connections to those deemed important individuals in advance is excluded; even before this, the selection of the core individuals is driven by their existing prevalence in historical sources, quantity of output, or the particular interests of the researcher. One of the appeals of a computational approach to these datasets is that it can flatten social or historical hierarchies, making visible links or individuals otherwise obscured by their more prominent neighbours in the network. This ego network approach certainly has

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[2] For examples of epistolary historical networks, see Ahnert and Ahnert, *Tudor Networks of Power*; "Networking the Republic of Letters"; special issue of the *Huntington Library Quarterly*, *Network Analysis and the Early Modern Archive*. On historical networks more generally see Ahnert, Ahnert, Coleman, and Weingart, *The Network Turn: Changing Perspectives in the Humanities.*

[3] See for an example that applies network detection algorithms to an early modern dataset, Hill, Vaara, and Tolonen 377–408.

its uses for targeted research but works against this flattening; its reliance on existing expertise and scholarship can make more unexpected connections harder to discern.[4]

A second method might be to start with a preexisting list, as one might, for example, check for membership of the Royal Society to find communities of learning. This provides a firm and readily available criterion for membership and already suggests avenues of further research through known structures, such as the internal committees of the Royal Society. However, since we have started with a predetermined membership, the approach is limited to what is already well known through existing scholarship or biography. The matter is further complicated by communities that existed over a longer duration, with members joining or leaving at various points. Merely noting that someone was a member of the Royal Society, for example, would not alone tell us whether they connected with any given other individuals, who may have attended different meetings; membership also involved a great variety of levels of involvement—from lifetime commitments to the occasional, curious attendee. More generally speaking, many communities simply do not have full records of membership, and they are more fluid in their establishment, flourishing, and disintegration.

For a third approach, there are a range of network science algorithms at our disposal that attempt to define communities quantitatively. These methods share a common goal, which is to find the optimal set of clusters in a network where the nodes within each cluster share more connections to other members of that cluster than to those outside it. Possibly the most popular is the Girvan-Newman algorithm, using the metric "edge betweenness," which cuts a network at those connections that tie different clusters together, labelling the remaining connected parts as individual communities. Another approach is called "label propagation," a simple but effective algorithm that assigns each node to the label of the largest number of its neighbours, continuing until a stable set of labels is found. A third approach is the Louvain method, which utilises the metric "modularity," measuring how well a set of community labels describes the actual clustering of a network. To begin with, each node is assigned to a community of itself alone. The algorithm then moves each node in turn to the community of its neighbour, recalculates the modularity score, and stops when the highest score is found. It then repeats the process with these new membership groupings, until the highest overall modularity score is found (Blondel et al. P10008).

Most community detection algorithms, however, require an individual to be a member of exactly one community (i.e., it is not possible to be a member of more than one community or none). They also leave little room for ambiguity. This is problematic for

[4] For good examples where one or two ego networks are used to comment more widely on epistolary communities, see Hotson, Ahnert, and Lewis 283–313; Burge 257–81.

more organic forms of interconnection because in many cases it will be either reductive or impossible to assign an individual to a single community marker. In addition to these general, conceptual problems, community detection methods generally have specific technical or statistical issues to consider. Label propagation, for example, is nondeterministic, which means it may return a different set of communities each time it is run, particularly for smaller networks. The Louvain method is known to get stuck in *local optima*, in essence making decisions early in the process that mean it cannot find the best overall solution.

How ought we thus to approach a cluster that has a certain level of coherence yet lacks a single defining characteristic, where simplistic inclusion or exclusion of members would demonstrably alter the nature of the community? For a solution we turn to the notion of family resemblance, which we present as a valuable methodological framework for dealing with ambiguously related or clustered groups.

Family Resemblance

Family resemblance is an idea developed by Ludwig Wittgenstein (1889–1951) across the span of his later philosophy during the 1930s and 1940s. It simultaneously operates as a precise philosophical concept, and as the ordinary use of the word in everyday language—that is, the multiple subtle ways in which members of a family may resemble each other (Wittgenstein *Philosophical Investigations* §67, §§164–235). Family resemblance as a scholarly tool has been taken up in various fields, especially where a balance must be maintained between difference, similarity, and identity, such as the philosophy of religion, education, machine learning, and business studies.[5] More recently, there has been a renewal of interest in Wittgenstein's work on the philosophy of mathematics, particularly in how applications of his arguments by analogy might pave the way for uncovering problems that current tools or terminology are inadequate to answer, or even define (Gibson and O'Mahoney 36–49). This deliberate open-endedness provides an appropriate starting point for our effort to apply family resemblance to the notion of community.

In his *Blue and Brown Books,* Wittgenstein introduces a shared set of characteristic features within a family as a way of accessing his philosophical method, emphasising differences and juxtaposition over a hunt for definitions:

> Imagine that someone wished to give you an idea of the facial characteristics of a certain family, the So and so's, he would do it by showing you a set of family portraits and by drawing your attention to certain characteristic features, and his main

[5] See, for example, Phillips; Vadera, Rodriguez-Martínez, Succar, et al. 67–74; Wittek and Kvernbekk 671–84; Leunbach 1–11.

> task would consist in the proper arrangement of these pictures, which, e.g., would enable you to see how certain influences gradually changed the features, in what characteristic ways the members of the family aged, what features appeared more strongly as they did so. (Wittgenstein *The Blue and Brown Books* 125)

In the 1920s, Wittgenstein had already taken this imaginary case in a practical direction and actually co-produced a series of superimposed photo portraits of his own family (**Figures 1** and **2**).[6]

Figure 1: These are portraits of the four siblings on which the composite photograph is based, from Wittgenstein's photo album: the sisters Margarete, Helene, and Hermine, and Ludwig Wittgenstein; the necklaces and blouses and Wittgenstein's shirt and jacket allow the identification of the individuals in the composite. Copyright: Wittgenstein Archive Cambridge.

[6] **Figures 1** and **2** are reproduced in Nedo 268–69. We are grateful to Michael Nedo for providing additional information about the images' provenance in correspondence.

Figure 2: This is a composite photo produced in the 1920s under Wittgenstein's instructions by Moritz Nähr, a family friend and famous photographer in Vienna in particular of the Secession and its artists. Copyright: Wittgenstein Archive Cambridge.

The careful overlaying of images produces a fiction of shared and contrasting features; some become more prominent, such as a similar shape of brow or nose, while others are softened or blurred. Family resemblance thus provides a reminder of how complex concepts are best not understood in terms of fixed and final definitions but as mutable and organic organising systems.

In the *Blue and Brown Books*, the term "family" is most often used to show when a single word or grammatical form seems to cover many cases that cannot be given a strict rule for inclusion or exclusion of a set—such as the concept of a "game" (and what constitutes a game) (Wittgenstein 17, 20, 33, 88, 119, 125). Wittgenstein's method involves provisionality of concepts and the recognition that not all boundaries are sharp—indeed, some are blurry, permeable, or tidal. This is the kind of view of our case study of community we hope to come to, avoiding the problems of defining a community that were raised in the introduction.

Wittgenstein's concept has been applied to large-scale data before in the areas of machine learning and Artificial Intelligence (AI). It is worth briefly elaborating on these instances, as our use outlined below attempts a radically different approach, suitable to detect and uncover communities. In a machine learning context, family resemblance has often been read as a synonym for "exemplar" whereby for a given dataset of exemplars, resemblance provides a contextualised measure that assists categorisation of further data. Rather than a yes/no fit into category A, B, C, and so forth, which lies at the heart of community detection algorithms, exemplars display a measure of "focality," which is a high match with data within a given category and a low match with data that falls outside it. In effect, machine learning conducts a form of comparison between sets of examples, with the capacity to refine comparisons as additional training on cases is completed. This fits with Wittgenstein's suggestion that sometimes simply assembling a set of examples is the fullest explanation we could give (see in particular *Philosophical Investigations* §§21–38).[7] One limitation of this approach is the necessity of preestablishing the exemplars in ways that are sensitive to the desired outcome and the nature of the data in question (Lesot, Rifqi, and Bouchon-Meunier 431–52).[8]

In sum, there are four general conditions that we have taken from Wittgenstein's concept and that are central to our method: there is no one shared characteristic between the members of our community, but an overlapping of a series of characteristics; we stress the continual provisionality or fluidity of our data treatment; we do not attempt to come to a conclusive definition of this community; and lastly, our community has no sharp edges but blurred boundaries that may shift to reflect a particular purpose or perspective. By applying these key principles, we move beyond the most common community detection algorithms in network science as well as machine learning (including AI), which operate instead on the premise of the best possible or plausible "fixed" position of members of the community or communities.

Part 2

The Case Study: The Dutch Republic in EMLO

In order to test the viability of the family resemblance method for capturing a community, we turn to a specific case study: the Republic of Letters. This vibrant

[7] This approach is clearly explained in Vadera, Rodriguez-Martínez, Succar, and Wu 67–74.

[8] See also Hanson and Bauer 343–72, see for a critique, Talmon, Fonteijn, and Braspenning 91–104.

community flourished from the fifteenth to the eighteenth century. Scholars, academics, artists, artisans, and aristocrats from various countries communicated, debated and struck up friendships via letter. However, these communities within the Republic of Letters, or indeed the Republic of Letters itself, are not easily defined. Connections were various and sometimes spontaneous; the methods, means, and intent of links varied enormously, and our textual records struggle to capture additional contacts through travel, gossip, the reading public, or in-person meetings. It has been pictured as an "imagined community" but one made up of many layered and varying networks (Van Miert, Hotson, and Wallnig 28). The diverse characterisations of the Republic of Letters in existing scholarship amply illustrate this complexity of definition and concept.[9] There is thus no straightforward way of quantifying or defining such activity, or how the participants perceived themselves to be part of their "community."

Within this broader notion of the Republic of Letters, there is an epicentre of dense connections within the Dutch Republic.[10] According to the definition of a community in network analysis given above—more connections within than outside this group—the Dutch corner of the Republic of Letters is a viable candidate of a sub-community of the Republic Letters as a whole. It is not, however, simple to say what this means beyond a basic commonality of geography. Confessional adherence, origins, profession, social standing, and intellectual interests diverged widely, and rivalry was as common as collaboration. Moreover, the members were heavily characterised by their mobility. Many prominent contributors had been born outside the Dutch Republic or had nomadic careers. Neither local birth nor term of residency provide therefore a telling characteristic for capturing membership, as examples such as Hugo Grotius (a famous humanist who spent most of his life in exile outside of the Dutch Republic) or Gerardus Joannes Vossius (another humanist stalwart at the Dutch universities but born outside the Republic) illustrate.[11]

Further, the community we are attempting to define is not limited to correspondence data alone. Even a hypothetical "perfect" community detection method, using letter metadata, would be inadequate. Often citizens of the Republic of Letters, especially in the small Dutch Republic, lived in close quarters and worked at the same institutions, so would not usually send letters to one another. Using the methods available for letter metadata—ego network analysis and community detection algorithms such as those discussed above—would therefore contain a sample bias of a different type:

[9] See for different representations, Searle 303–7; Burke 395–407; Goldgar, *passim.*

[10] See for work on the Dutch Republic as a hub of intellectual exchange: Bots 10–11; Prögler; Blok, *Isaac Vossius en zijn kring*; Blok, *Nicolaas Heinsius*; Van Miert and Jorink.

[11] For more biographical information, see Rademaker; Nellen.

They primarily tell us which groups sent letters to each other in more volume than to those outside. Since letters are largely a technology of long-distance communication, the results might even be precisely the opposite of a Dutch-focused community, and at the very least would understate the closeness of those working in the same city or university. It is therefore an excellent test case for the family resemblance method. There is no one characteristic that joins those we might consider to be part of the Dutch Republic of Letters, nor do its members seem to have conceived of any fixed statute of membership, yet the particularly dense network of letter writers does suggest a sub-community.

Early Modern Letters Online

For this case study we are primarily using the database Early Modern Letters Online, based at the University of Oxford. This contains letters received and sent in the period 1550–1750, with a particular focus on the Republic of Letters. The database has been built, and continues to be developed, through collaboration, the efforts of volunteers, and several funded projects. It is by no means a complete representation of the Republic of Letters, but it is substantial enough to be used for quantitative analysis and it is among the best resources of its type.[12] The dataset that is used in this article (taken from metadata of 2019) consists of 21,228 people and 151,769 letters. The database reflects its own particular priorities, such as the consequences of availability of data, the interests of contributors, and the directions of funding. Nonetheless, for our question of capturing the Dutch corner of the Republic of Letters, there are several reasons to use it as a contextualising dataset.

First, we acknowledge the practical problems of availability. Several extensive databases such as the Electronic Enlightenment are behind a paywall and therefore not readily available for analysis. As part of the Networking Archives project, an Arts and Humanities Research Council–funded collaborative project with Ruth Ahnert, Sebastian Ahnert, Philip Beeley, Howard Hotson, Miranda Lewis, Esther van Raamsdonk, and Yann Ryan, three datasets will be combined, leading to a total of 450,000 correspondence records: the Tudor State Papers, the Stuart State Papers, and EMLO.[13] Once fully curated, this metadata will be open access and available for others to use and replicate our findings.

Second, the data in EMLO overlaps very significantly with our case study in geographical and chronological terms. There are two epicentres in the database: England

[12] For a list of contributors of metadata to EMLO, see "Contributors," *Early Modern Letters Online*, http://emlo-portal.bodleian.ox.ac.uk/collections/?page_id=2259.

[13] "EMLO," *Cultures of Knowledge*, http://www.culturesofknowledge.org/?page_id=28.

and the Dutch Republic. **Figure 3** reveals the geographical location (sent and received) of letters within EMLO for the period 1600–1700. Most data points are concentrated in England (the southeast in particular) and the Dutch Republic, with another smaller hotspot in Paris. This is further supported by the density of correspondence, that is, the connections from one individual to others. **Figure 4** demonstrates that many of the European connections were to and from the Dutch Republic and that there was also a particularly busy network of letters being exchanged internally. Furthermore, EMLO is already successfully used for network analysis, albeit with different foci, showing the suitability of the data for these kinds of enquiries.[14]

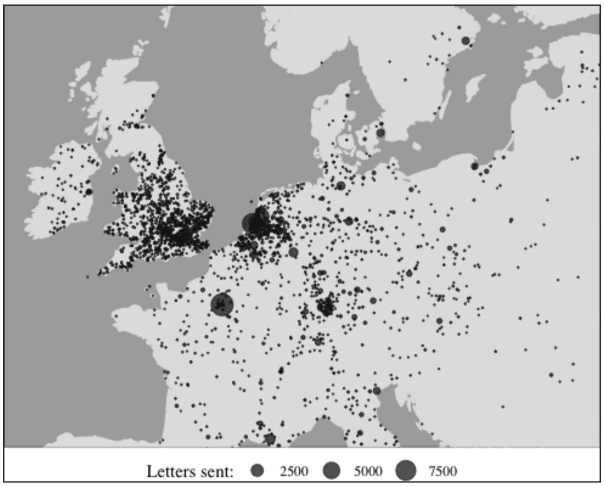

Figure 3: A map shows the distribution of letters, sent and received, in EMLO, 1600–1700.[15]

Figure 4: These are connections between letter writers in EMLO, focused on London, Paris, and the Dutch Republic, 1600–1700.

[14] See for example, Hotson, Ahnert, and Lewis; Ahnert and Ahnert 399–416; Van Raamsdonk and Ahnert 81–110.

[15] All figures in this article are bespoke and made by Yann Ryan.

An additional advantage of EMLO is its stringent editorial policies; the data is unusually clean and carefully curated. The dataset has strict processes to ensure consistent capture of key features, such as identity of sender and recipient, and mentions of other known figures. Dates and calendars are standardised, and disambiguation of individuals with multiple entries has been carried out. While acknowledging the limitations of any given dataset, EMLO provides a good model and resource for our current purposes.

Part 3

Experiment Parameters: EMLO and Wikidata

On then, to our family resemblance method. Our starting point is to establish a set of externally collected characteristics—equivalent to very broad family traits—which can then be used to identify clusters of members sharing one, several, or even none of these characteristics. The experiment has two primary rules reflecting Wittgenstein's concerns. The first of these is a non-hierarchical approach to the selected characteristics, where we do not, for example, presume greater importance for university association over languages spoken. The second is that we do not hold any given characteristic to be essential; in keeping with the family resemblance model, different features will come into view at different points, assuming importance through their position in the network or relative to other clusters of characteristics. We will quite deliberately not come to a single definition of this community, nor is there a sharp boundary between this community and the rest of the Republic of Letters. This frees us from the constraint of a letter-based community detection method, which would exclude several candidates whose correspondence is not held by the archive or could privilege more prolific contributors.

The characteristics for each individual are subsequently derived from Wikidata. Such information will not usually be available from the content of letters themselves, and it would not be feasible to manually provide full characteristics to all the possible members, which would be in the thousands. A subset of EMLO has therefore been created: all those with data available on Wikidata. We filtered the people in EMLO with Wikidata links for persons born between 1500 and 1700, leaving us a list of 2,392 individuals with usable amounts of information. This data is downloaded, and the set of characteristics on which the analysis will be based is drawn up, coined our "community resemblance" method (see **Figure 5**). Finally, the results of this are presented in multiple and various ways to aid visualisation and further investigation of the emerging linkages.

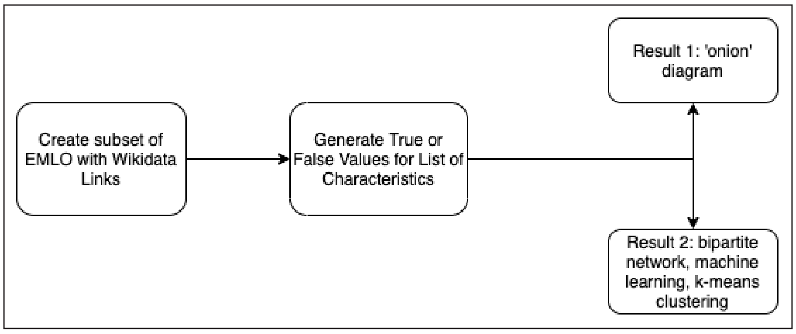

Figure 5: This is an overview of the "community resemblance" method.

Wikidata is a "collaboratively edited knowledgebase" drawn from Wikipedia (Vrandečić and Krötzsch 78–85). It is an example of a "knowledge graph," a data model in which information is linked through a simple semantic structure—a database of "facts." Wikidata is one of the largest knowledge graphs in the world, containing over 100 million items.[16] At least basic information is available for many individuals, which includes their birth and death dates, place of birth, education, and occupation. An inherent limitation in this data is that those for whom it is possible to obtain data either in EMLO or Wikidata will inevitably be those about whom more is known; this is unavoidable since for some EMLO entries we only have the most basic metadata (sender and receiver, date, and possibly place). However, as our findings will show, the categories of data used and the sample size remain large enough that we can avoid only working with famous names or specific cohorts.

The quality of the data from Wikidata is admittedly not as high as for EMLO, because it is often drawn from the collaboratively edited Wikipedia and dependent on basic semantic structures—for example, the specific mention of someone having Dutch to capture their language abilities. However, the quality remains usefully high and adequate for our research question. In fact, a slight vagueness around the "facts" about individuals fits perfectly well with the family resemblance model, where the categorisation of features or cases is often less clear cut than a simple binary. Since no single characteristic is a requirement for membership of the group, missing or inaccurate information for a small number of cases or characteristics will not significantly alter the results.

The first concern is how to establish the list of characteristics, such that a large number of individuals can usefully be included in the analysis while still being specific enough for the results to show something. We began by assembling a set of characteristics, each sufficiently broad to avoid cherry-picking but together holding

[16] For latest totals, see "Wikidata: Statistics," *Wikidata*, https://www.wikidata.org/wiki/Wikidata:Statistics.

some relevance for our geo-temporal target. Three criteria informed this decision: the likelihood that such information would actually have been recorded in Wikidata; that the category would be likely to yield a yes/no answer; and that the characteristics would have an intuitive general link to the Dutch Republic, such as having the Dutch language. For practical purposes, the list was capped at 10 characteristics. Far fewer would be unlikely to show any great patterns in the data, and far more would likely individuate the data too much. Our 10 characteristics were:

1. Born in the United Provinces (or Northern Provinces before Dutch Independence)
2. Died in the United Provinces
3. Worked at one or more Dutch Universities
4. Latin listed as a language
5. Dutch listed as a language
6. Protestant
7. Described as linguist, philologist, historian, theologian, classical scholar, politician, or philosopher
8. Described as an author
9. Has an entry in the Digitale Bibliotheek voor de Nederlandse Letteren (DBNL)
10. Has an entry in Het Biographisch Portaal van Nederland

The first eight categories are basic biographical data suggesting Dutch links or academic connections. The last two are a measure of whether their presence has been deemed important to historiography of the Dutch Republic in two major modern databases. Digitale Bibliotheek voor de Nederlandse Letteren collects historical texts and biographies of importance to Dutch linguistic, literary, and cultural history, covering the entire history of the Dutch language.[17] Het Biographisch Portaal van Nederland has a dataset of 80,632 notable figures in Dutch history and is hosted by the KNAW-Institute.[18]

Over the 10 characteristics, the 2,392 individuals generated 3,511 positive entries in total. **Figure 6** shows the total number of individuals holding a total of characteristics (0 to 10, in any combination). No single person had all 10 characteristics, and 718 had none. **Figure 6** also shows for each of the characteristics how many individuals had a positive record (e.g., 1100 fit category 7 and have been noted as a linguist and/or philologist etc; 488 are listed as having Latin, category 4).

[17] See the Digitale Bibliotheek voor de Nederlandse Letteren at https://www.dbnl.org/.

[18] See Het Biographisch Portaal van Nederland at http://www.biografischportaal.nl/.

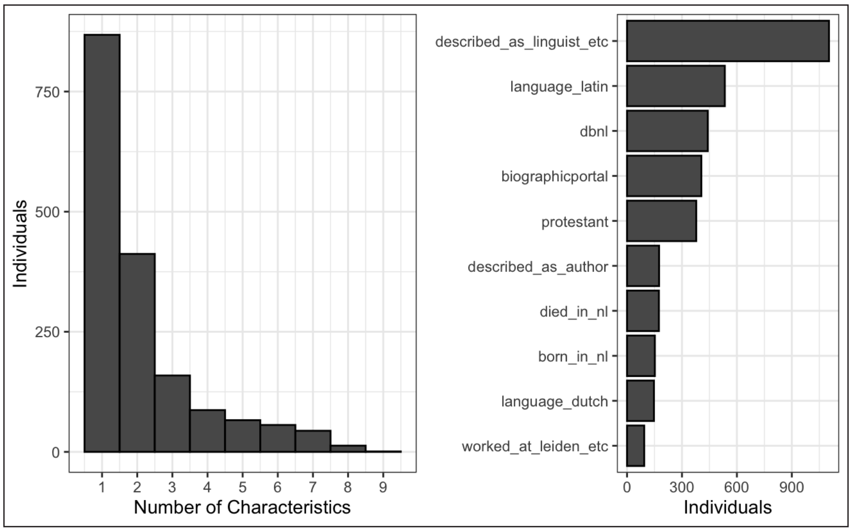

Figure 6: These are summary statistics of the extracted characteristics. The chart on the left shows the distribution of characteristics (most have 1). The chart on the right shows the total number of individuals with each characteristic.

A very simple observation from these numbers is that there is great variety between the members of the dataset and that no one characteristic could usefully define the group alone. This is to be expected given the complex nature of the Republic of Letters and does fit with our expectations.

Community Resemblance

This section presents a series of methods that apply the family resemblance approach, each making it possible to view the data in a different revealing way. They reflect a set of interlinked attempts to represent the Dutch corner of the Republic of Letters, creating a background against which individuals and their communities come to make sense. This is especially valuable in the case of lesser-known individuals, whose connections may not be so well understood, and for attempting to establish something of the character of the Republic of Letters from the ground up, rather than starting with the most prominent names and events.

First we ranked and grouped our individuals based on how many of the 10 characteristics they possessed (see **Table 1**). As noted, no one person held all 10 characteristics; 1 person has 9, and 12 have 8 characteristics. Intuitively, persons with a higher score, or higher number of characteristics, are likely to be more deeply embedded in the various mechanisms that allowed the community to operate and might be called the "core" group, with persons holding fewer characteristics fanning out around them. This ranking is not designed to suggest that some individuals are "more" Republic of Letters than others, but merely a way to make sense of the results.

Name	Characteristics
Cats, Jacob	9
Bidloo, Govard	8
Heinsius, Daniel	8
Barlaeus, Caspar	8
Polyander van den Kerckhoven, Johannes	8
Voet, Gijsbert	8
Amama, Sixtinus	8
Cunaeus, Peter	8
Episcopius, Simon	8
Brandt, Geraert	8
Revius, Jacobus	8
Hoornbeeck, Johannes	8
Til, Salomon van	8
Boerhaave, Herman	8

Table 1: These are individuals with 8 or 9 characteristics out of 10.

Apart from noting that no one person had all 10 characteristics, which indicates that the list is not too general, we can see from the highly ranked persons that the categories capture some of the well-known individuals we would expect to find in any account of (scholarly) members of the Dutch Republic of Letters. The only person counting 9 out of 10 characteristics is Jacob Cats (1577–1660), an enormously influential person in Dutch intellectual history, as poet, jurist, and diplomat. Of the other high-scoring people included in Table 2, a similar educated vein can be found: the writer and royal physician Govard Bidloo (1649–1713), for example. Some of these, such as Bidloo, are much less written about than the Dutch humanist stalwarts and supposed key members of the Republic of Letters, such as Hugo Grotius or Gerardus Joannes Vossius. Focusing therefore on characteristics rather than volume of letters already highlights less-studied individuals. A further important observation is that no single category of people comes to the fore, as would be the case if this were a more homogenous community. Not everyone was born in the Netherlands, there is no religious consensus between members, different education levels feature, and there is considerable variation in dates. For example, Johannes Polyander van der Kerckhoven (1568–1646) originated abroad; Daniel Heinsius (1580–1655) and Simon Episcopius (1583–1643) were at opposite poles of the Arminian controversy in the Dutch Reformed Church; the physician Herman

Boerhave (1668–1738) worked at the same university as Van der Kerckhoven, but only after the latter had died. Several individuals had no university affiliation at all. Rather than a homogenous group of core people, we see a patchwork community of friendships and rivalries, employment and expertise, politics, and personal history, but all with very strong connections to the Dutch Republic one way or another.

This top group merely represents the most visible part, but it is important to retain blurrier edges to our notion of community if we are to avoid artificially excluding potential members.

Visualising the Dutch Community

Though generally involving simplification, data visualisations can help human readers navigate and categorise without having to assign specific labels. The fuzziness of data visualisation can in this case be used to our advantage. Here we propose and evaluate two methods: a circular diagram with layers like an onion and a bipartite network based on shared characteristics. To render further cases visible, this subset of EMLO (those with Wikidata links) can be visualised based on the counts of characteristics.

In **Figure 7**, each individual is situated in a layer corresponding to the number of characteristics held, and in whatever combination. These layers are laid out as circles, like an onion, with those nearer the centre having a higher score. The size of each individual's node represents their volume of correspondence. Lines connecting the nodes illustrate correspondence between them, again weighted. It is noticeable that a large proportion of the most prolific individuals in the dataset are placed near the centre (e.g., Constantijn Huygens and Gerardus Joannes Vossius), though it is far from exclusively made up of these members. Herman Boerhaave, for instance, only has a small correspondence. This speaks to the considerable presence of the Dutch part of the Republic of Letters in EMLO.

What the onion diagram cannot show us with great clarity, however, is the effect of specific characteristics. This is a deliberate means of simplification to illustrate how the characteristics as a whole might outline a community. However, this on its own could give the wrong impression of what having a high number of characteristics means, or what closeness to the core reveals. The prominence of several of the most important individuals in terms of total correspondence need not indicate that they were central to the group as a whole nor even a cluster within it. It could equally mean that their social standing and diverse expertise connected them with several of the groups, including less-central members. The next level of detail is to look into groups of shared characteristics, for example all those who are Dutch, linguists, and Protestant and whether these produce coherent or corresponding groupings. In order to do so, we turn to the bipartite network.

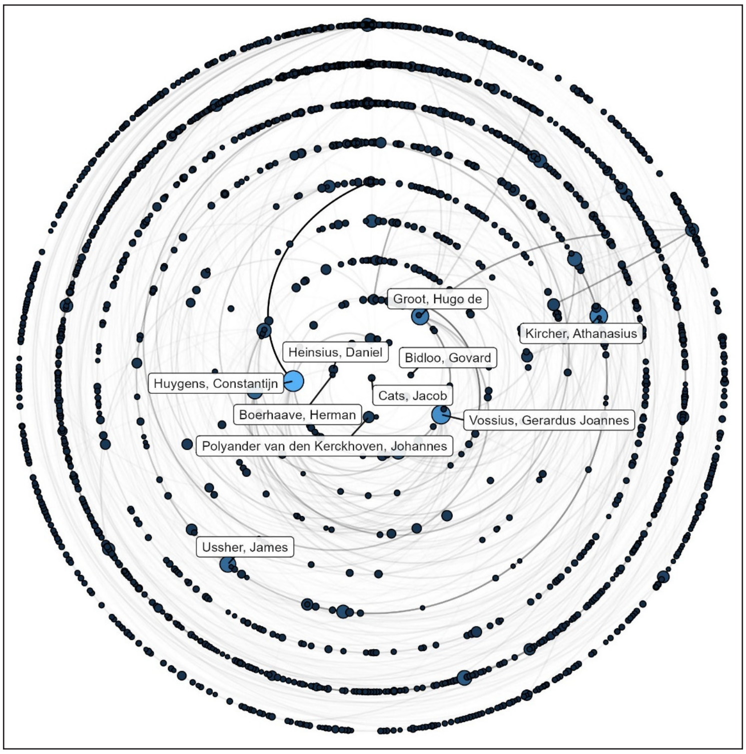

Figure 7: This is an "onion" diagram, with individuals represented as points and placed in a layer according to the number of characteristics. The positions within each layer are randomly set. The outer layer contains those with no characteristics (but with EMLO Wikidata links), the next layer those with one, and so forth until the centre, where those with all 10 characteristics would be found, had there been any. Each point is sized and coloured by the total number of letters written and received in EMLO. The curved lines between points visualise the number of letters in the database sent between two individuals. Some key individuals, either those with the most connections in EMLO or with the most characteristics, are labelled.

Community Resemblance and a Bipartite Network

A bipartite network consists of two node types and only allows connections between nodes of different types (see the red and blue nodes in **Figure 8a**). These networks often describe associations, for example actors and the films in which they appear. Bipartite networks can be projected, which means that we create a new network of just one of the node types with weighted connections between these nodes that signify the number of shared entities of the other node type (see **Figure 8b** for the different connections between the individual nodes). With actors and films we could create a projected network of actors in which two actors might be connected by, for example, a connection of weight 3 because they appeared together in three different films. A projected network of films would connect two films with, for example, a weight of 4 if those films had four actors in common. An alternative way to think about the projected network is to consider a multigraph, a network in which two nodes can be linked to each other by more than one network connection. In the above example of the projected network of actors, the two actors would be linked by three separate connections, one for each film. Our Dutch individuals and the characteristics they hold can be used for such a projected bipartite network.

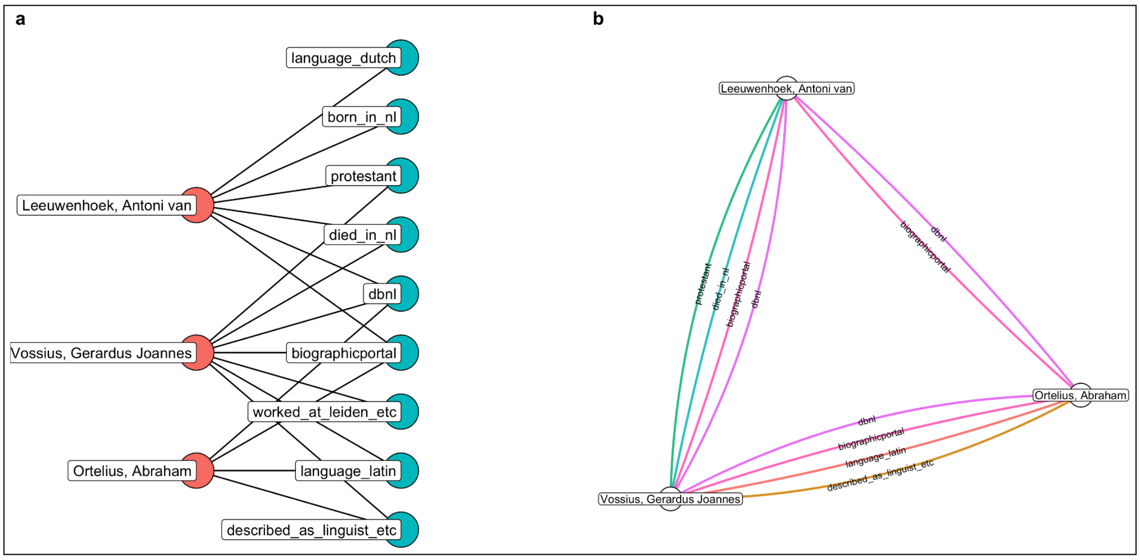

Figure 8: First, a bipartite network connects individuals to their characteristics as seen in (a). In a second step (b), the network is projected, directly connecting individuals based on overlapping characteristics. The resulting multigraph draws a separate line for each overlapping characteristic so that in the toy network, Antoni van Leeuwenhoek is connected to Abraham Ortelius by 2 separate lines or characteristics, Ortelius is connected to G.J. Vossius by 4 characteristics, and so on. This is the basic building block of the network discussed below.

Figure 9 reveals the individual characteristics and their connections with the nodes, highlighting each shared characteristic individually. This helps to show why the clusters have formed in a particular way. **Figure 10** shows the full bipartite network in operation (overlaying each individual characteristic as seen in **Figure 9**), with specific individuals highlighted. In order to maintain a level of legibility in the multigraph (**Figure 10**), a threshold of 5 characteristics is imposed, in order to centre our attention on a core of 172 individuals. It is important to remember that we are focusing on the densest part of the projected network, with individuals who share many characteristics with each other, but that the remainder of the archive is still part of this bipartite network, with lower-scoring individuals at the periphery. The projected network of individuals highlights specific clusters within the community that reflect similar combinations of characteristics. The constituents of these clusters may not have been in direct contact with each other (which can be separately investigated via the correspondence data) but were nonetheless part of the same community. Since overlaps in interests, background, or profession make it more probable that individuals knew each other, an overview of these similarities is likely to suggest clusters of interest.

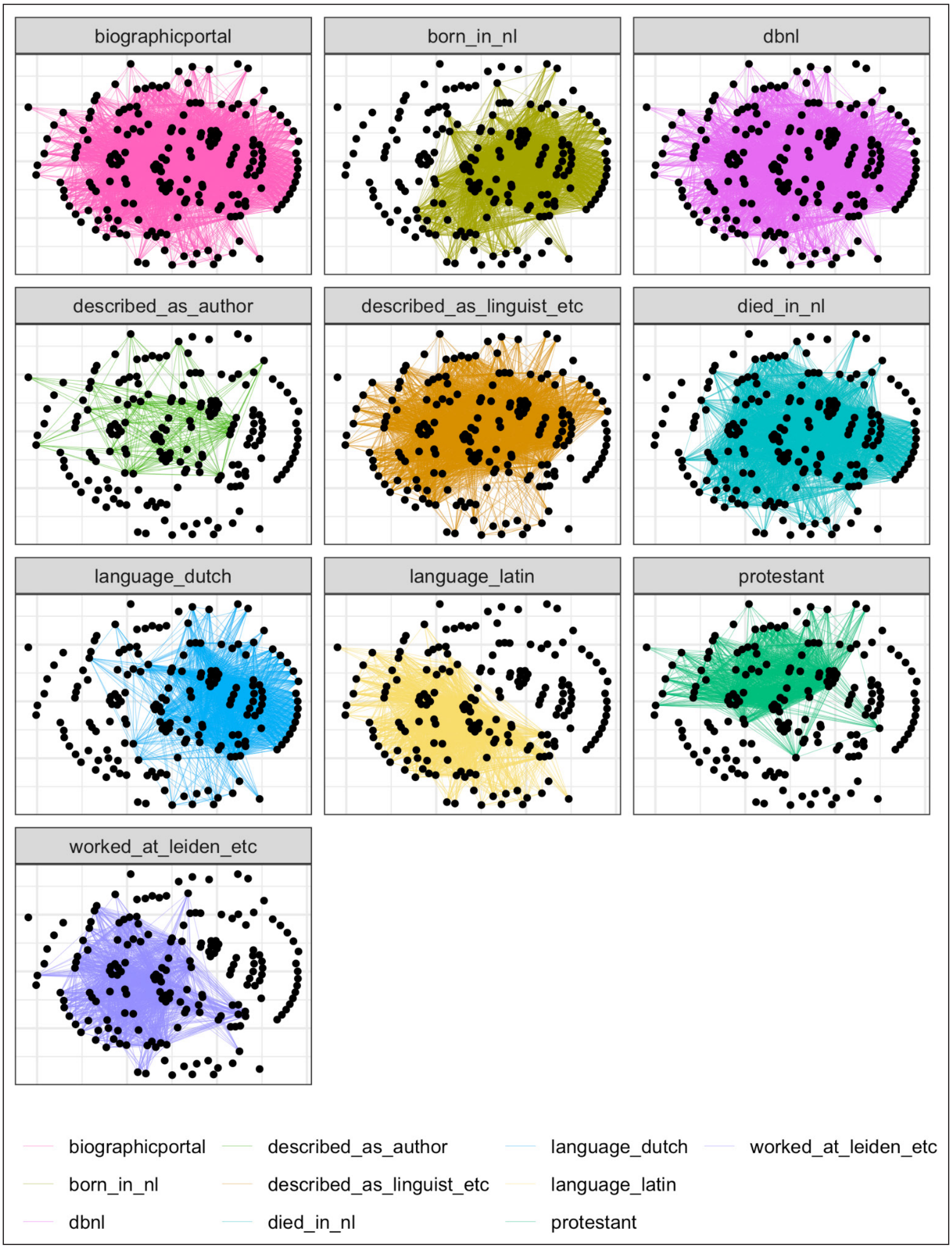

Figure 9: In this version of the graph, nodes were kept in the same position and connections were drawn for each type of characteristic separately. This shows, for example, that those labelled as Protestant tend to be clustered in the top left of the graph, those who spoke Latin in the bottom left, and so forth.

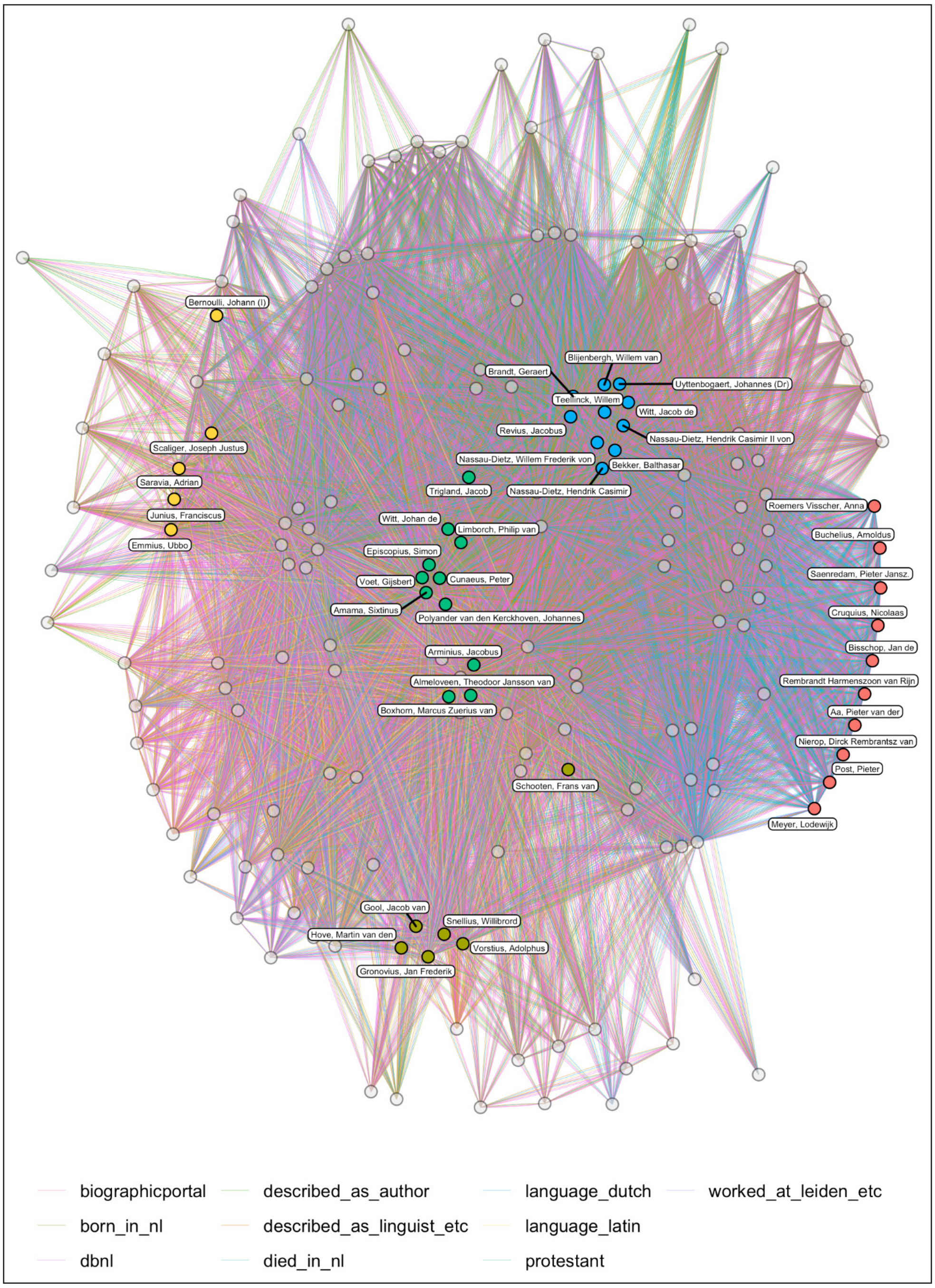

Figure 10: A multigraph of a bipartite network demonstrates the core of the Dutch community who share more than 5 characteristics. Each node (circle) is an individual found in the EMLO database. Each edge (line), between two nodes shows that the pair shared that particular characteristic. Nodes are placed by an algorithm that determines position based on connections to each other. This means, in practice, that groups of nodes with many shared characteristics will be clustered together. As the number of labels make the full graph difficult to read, five relevant clusters have been highlighted and labelled.

What can these clusters reveal about the Dutch Republic of Letters, the community we are trying to capture? Generally, those in the lower half of the multigraph were born in the Netherlands and had the Dutch language as a shared characteristic, whereas the top half of the graph has a strong preponderance of people who were born outside of the Netherlands. Many were Protestant refugees, with strong links to Dutch academic institutions, such as the contemporaries Ubbo Emmius (1547–1625), Joseph Justus Scaliger (1540–1609), and Franciscus Junius (1545–1602). They certainly knew one another, demonstrating that our clustering method indeed finds concrete communities.

Within this divide, some specific clusters are noticeable. In one section of the multigraph (nodes coloured red in **Figure 10**), there is a clear cluster of artists and cartographers, with figures such as Rembrandt van Rijn (1606–1669) and Pieter Post (1608–1669). They are relatively far removed from those with strong connections to the Dutch academic institutions but have in common being born and having died in the United Provinces, and the Dutch language. One cluster (coloured green in **Figure 10**) combines both Dutch nativity and links with Dutch academia; six Dutch mathematicians and botanists appear who went to Leiden as students or worked there as professors, or in some cases both. The combinations of characteristics thus lead to collections or clusters of individuals that are in many cases remarkably similar in background, interest, confession, and profession. It is likely that they would have known each other (and in many cases, we know they did from other sources).

Not all clusters are, however, so clearly defined. We sometimes find two different but coherent groups within the same cluster, such as in the cluster with blue nodes. This is a mixture of aristocrats, stadholders of the Nassau-Dietz family, and preachers, such as Jacobus Revius (1586–1658) and Johannes Uyttenbogaert (1557–1644).[19] They had Dutch origins, the language, and a strong presence in biographical sources in common. At the centre of the graph (coloured green), there is another sizeable cluster with some commonality but also with outliers. The cluster is characterised by Dutch theologians, who were divided within themselves by soteriological differences, such as Jacobus Arminius (1560–1609) (Remonstrant) and Franciscus Gomarus (1563–1641) (Contra-Remonstrant). The latter is not part of this cluster but is placed a little farther away. At the centre we find Arminius, joined by several close supporters, such as Simon Episcopius (1583–1643) and some more radical figures, such as Sixtinus Amama (1593–1629) and Philip van Limborch (1633–1712), who we might also consider here as (radical) Remonstrants, albeit they were not contemporaries. On the opposite spectrum, Gijsbert Voet (1589–1676), Johannes Polyander van den Kerckhoven, and Jacob

[19] See for the Nassau-Dietz dynasty, Nissen 15–30.

Trigland (1583–1654) were prominent Contra-Remonstrants. Despite the intricate theological differences, these men would have similar combinations of characteristics (such as Dutch and Latin as languages, being described as Protestant, and having been born in the United Provinces), bringing them into close proximity—as they were in real life. Johan de Wit (1625–1672) is an example of an outlier. He functioned as a Grand-Pensionary of Holland, the highest Republican political office, for nearly twenty years. He closely matches the same unique set of characteristics, but for obviously different reasons. His example illustrates that these sub-clusters are not of coordinated groups but rather point to a commonality of circumstances. The juxtaposition of these diverse figures suggest proximity in terms of interests, linguistic skills, education, and profession, even if they would rarely be grouped together through biography alone.

These sub-clusters allow us to visualise sets of similarities and points of difference that would be obscured if working from individual biographies or a single set of commonalities. The arrangement of the nodes in order to display the bipartite network in two dimensions echoes Wittgenstein's earliest presentations of family resemblance, that is, the arrangement of pictures in order to bring particular features into view (**Figures 1** and **2**). This method allows us to bring combinations of characteristics and connections to the fore—individuals' backgrounds and expertise—without a reductive insistence on a single essential feature or connection. In particular, the bipartite method suggests clusters within a nonhomogeneous group that may not have known each other but are very likely to have moved in similar circles, and perhaps have known *of* each other. This, we suggest, paints a more realistic picture of how a community operates, with small, fluid clusters merging and splitting from larger structures, and with individuals forming bridges between multiple sub-networks.

Conclusion: Defining the Dutch Community

Within the constraints we have established of avoiding a strict and permanent boundary around a putative Dutch Republic of Letters, the results from the methods described certainly capture an active, interconnected, and diverse core operating within the Dutch Republic but also well-connected to those outside it. There are family resemblances of frequently occurring characteristics or groups of characteristics that provide us with a fuller picture of the community's interconnections, creating clusters of individuals within a network that is certainly not homogeneous. Strong differences between members in politics, faith, and social standing remain and may have driven some of the notable cases of core members not corresponding with each other directly, despite their likely acquaintance by other means. As our analysis above shows, applying the historical information we already have about prominent individuals and society at the time allows us to better understand why groups of individuals are clustered together, suggesting further avenues of refinement along lines of scholarly interest. As ever, the real strength of such a method is bringing together traditional scholarship and innovations in large data approaches in mutual support, rather than prioritising one over the other. Here we find a balance between the roles of viewing the community at a distance and the supplementation of being able to compare and contrast at close range.

Out of 2,392 individuals for which we have linked Wikidata to EMLO, 172 individuals (those with 5 or more characteristics) might be considered the core in question. Our analysis did not rely on letter data in order to avoid potential biases in the archive, where those with large letter correspondences are often prioritised. Having established that core, we can study the number of letters within this sub-community. The 172 individuals wrote a total of 22,364 letters contained in EMLO, out of about 65,000 attributed to the 2,392 with Wikidata links. We can thus firmly assert that the Dutch corner of the Republic of Letters was extremely prolific, accounting for more than a third of the total letters. This degree of activity is all the more remarkable when considering its relatively narrow geographical space. While our method of analysis is not dependent on any one archive, and deliberately avoids relying fully on correspondence data, our findings also emphasise the importance of Dutch contributors to the Republic of Letters within the EMLO database; even though they are relatively low in number, the output and degree of connection is very high.

Our bipartite method shows that analysis of large datasets of individuals on the basis of sets of simple characteristics can be an effective indicator of network closeness. Despite noticeable differences within the core group of individuals holding a high number of our projected characteristics—and no one person holding all of them—clusters and continuities can be discerned, including patterns of correspondence between core members and those less centrally placed. These patterns have tended to confirm, and in some cases extend, existing knowledge of connections between well-known individuals and their circle, independently of detailed biography or reference to famous names. This way of thinking about communities through data is consequently a useful measure of interconnectivity of a given (or supposed) community and allows the researcher to begin from a more open and provisional standpoint.

The same methods could be applied productively to many other contexts. The approach is flexible and provides a pragmatic means to overcome limited availability of data, especially for difficult-to-define communities where several unrelated variables play a role in contributors' inclusion. The method would be suitable for other datasets with similar information, such as correspSearch or the State Papers Domestic

1547–1649: Tudor and Stuart government papers in the National Archives of Kew.[20] It could equally be applied to datasets outside of the early modern period, such as the Electronic Enlightenment, Letters to Loved Ones, or Epistolae.[21] Beyond letter data, the method can be useful to uncover different types of communities. One could think of the English Short Title Catalogue (ESTC), a database holding bibliographical information about printed material pre-1800.[22] It could crucially supplement existing knowledge on author communities and networks, for instance those based around genres or the networks of authors working with specific publishers.

We have sought to demonstrate that Wittgenstein's concept of family resemblance suggests an alternative approach to definitions of community by allowing the characteristics of likely members to emerge and speak for themselves as much as possible. Our findings here are twofold. First, the clusters that have been uncovered in the network reveal something community-like in the Dutch corner of the Republic of Letters, densely interlinked yet far from uniform. It is a view of a community that is known to be difficult to define, yet it can be tested through combinations of broad characteristics and shows consistent clusters and sub-clusters. Additional research can analyse the different clusters within our Dutch community, delving deeper into unknown or surprising members. Second, this method can be applied to create or substantiate a background against which to set the individual members. While acknowledging that this background is itself responsive to our different applications and input, it is built from inherent features rather than an imposed definition. One important factor is that this approach does not require any one individual to be included or excluded from group membership but allows for different types of membership. Like family resemblances, some members will display more or fewer familiar traits, but none are essential to membership. The inherent incompleteness that Wittgenstein recognised as integral to any living society or language insists that recognition is perspectival and contextual; it provides historians with insights into the Dutch Republic of Letters that may inspire reconsideration of dominant historical narratives and allow us to turn our attention to the roles and connections of lesser-known contributors to the intellectual milieu.

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[20] The project Six Degrees of Francis Bacon, see http://www.sixdegreesoffrancisbacon.com/?ids=10000473&min_confidence=60&type=network; For the State Papers, see, https://www.nationalarchives.gov.uk/help-with-your-research/research-guides/state-papers-domestic-1547-1649/.

[21] Read more about the Electronic Enlightenment: Letters and Lives at https://www.e-enlightenment.com/; the Imperial War Museums at https://www.iwm.org.uk/history/letters-to-loved-ones; and Epistolae at https://epistolae.ctl.columbia.edu/about/.

[22] See Hill, Vaara, and Tolonen for an example of applying community detection algorithms to the English Short Title Catalogue.

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The authors have no competing interests to declare.

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Esther van Raamsdonk: conceptualisation, methodology, data analysis, writing; original draft, writing; review and editing

Yann Ryan: conceptualisation, methodology, network analysis and visualisations, writing; original draft, writing; review and editing

Michael D. Rose: theory, writing; original draft, writing; review and editing

Sebastian E. Ahnert: conceptualisation, methodology, and software

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