Partitioning communities of co-submissions of documents in the Dutch House of Representatives

Heine, Michael M.G.

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Tilburg University

Eindhoven University of Technology
Department of Mathematics and Computer Science

Tilburg University
Tilburg Law School

Partitioning communities of co-submissions of documents in the Dutch House of Representatives

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Michael Heine

Supervisor:

Pim van der Hoorn

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Abstract

This paper looks into the co-submissions of documents by Members of the Dutch House of Representatives using a network approach. The main focus is on community detection, whether clear partitioned communities are to be found in the network and whether these are insightful. Also, this research checks if and how detected communities can be related to the political parties. For this analysis, a bipartite network with the document and politician node sets is used as a basis.

Keywords: bipartite network, unipartite network, community detection, Louvain algorithm, legislative collaboration

Contents

Chapter 1

Introduction

This first chapter explains the topic and research of this paper, introduces the research question and goal, and provides an overview for the rest of the paper.

1.1 Context and Topic

Due to the advancements in Network Science in recent years, there has been a greater focus on applying a network approach to political data, specifically, co-submission ties between Members of Parliament. There have been studies conducted that analyse legislative collaboration using a network approach. Briatte (2016) has analysed twenty parliaments in a brief note in a partially similar way as this paper will for the Dutch Parliament. Also, different kinds of methods for analysing political data have arisen, e.g. Discourse Network Analysis which focuses on the discourse between political actors (Leifeld, 2017) but also Semantic Networks (Yang & González-Bailón, 2018). However, such methods have advanced the role of Network Science within the political field. Historically, these fields have not been overlapping often but due to new methods and the availability of more political data, this seems to be a thing of the past.

This paper will investigate the state of co-submissions on motions, amendments, and bills (from here on referred to as documents) among the Members of the Dutch Parliament (MPs). This research focuses specifically on the Dutch House of Representatives. It will analyse the co-submission ties between MPs to see if any communities can be found. Furthermore, political parties will be compared to see if certain political parties can be matched to communities found for the co-submissions. Existing research provides different results. Hric, Darst, and Fortunato (2014) find that often networks do not have clear 'ground-truth' matches the detected communities, whichever community detection algorithm is used. However, other research indicates that matches between communities and political parties can be found (Cherepnalkoski & Mozetič, 2016).

In a unipartite network, the nodes of the network are similar to one another. A social network of Instagram accounts where the edges indicate whether one account is following another and where nodes are Instagram accounts is a unipartite network since all nodes are the same unit, an Instagram account. A bipartite network on the other hand consists of nodes of different units. Documents can be a type of node and MPs can be another type of node. Edges can only connect a node of the other type, so MPs can be tied to documents.

Bipartite networks can be used for co-submission ties of documents and MPs (Lee, Jo, & Yoon, 2014) but it is often used for other (similar) research as well, like analysing global governance structures (Kim, 2020). Another study where they used a bipartite network similar to this research has been conducted in New Zealand (Curran, Higham, Ortiz, & Filho, 2018).

In the next section, the research question of this paper will be introduced. Then, the methods chapter will describe the dataset used in this research. It will also explain the data collection, data cleaning, and pre-processing steps taken to obtain the dataset. Next, the topic of networks is further explained and the bipartite and unipartite networks used to analyse the data are created and explained. Lastly for the methods chapter, community detection and the approach taken is explained. After this, the results will be shown and described in the results chapter. The next chapter, discussion, will then interpret the results, identify and list the limitations of this research, and provide suggestions for future work. At the end, the paper will be conclude by the conclusion chapter.

1.2 Research Question

This paper focuses on using a network approach to find communities in the co-submissions of MPs. It wants to find the communities that can be detected. More importantly, it will then compare the communities to the political parties the MPs belong to, to see if these match.

Therefore, research question of this paper is:

Are communities of Members of the Dutch House of Representatives that co-submit documents similar to the political parties?

Chapter 2

Methods

This chapter explains the dataset used for this research, where it was obtained, how it was collected, and what pre-processing steps were taken. Furthermore, the basic principles of networks, and specifically bipartite networks, are explained. The chapter also explains how networks are used for this research and how they were created. Lastly, community detection and the specific method used to for the network are explained.

2.1 The Data

This section will introduce the data that has been used for this research. It has been divided into three subsections: Data Collection, Data Cleaning and Pre-processing, and Simple Statistics on the Data.

2.1.1 Data Collection

The data for this study has been collected from the website OpenKamer.org (*Open Kamer*, n.d.) and mainly includes information on documents submitted and voted on by MPs. As an independent and non-commercial website, OpenKamer.org uses open datasets from Open Data Portaal using the OData API of the Dutch House of Representatives, wikidata.org, and overheid.nl. The data has been scraped from OpenKamer.org using the Web Scraper Google Chrome extension *Web Scraper* (n.d.). It should be noted that only documents which were voted on by the House are included in the dataset.

The following data has been collected has been collected for this research:

1. The title of the submitted document. The title is written in Dutch and is used to identify the document. The actual content of the titles are not used for further analysis in this research.

2. The politician(s) that submitted the document. Documents have to be submitted by at least one politician and can also be submitted by multiple politicians. The first and last names of the politician(s) that submits the document are recorded.

3. If applicable, the title of minister or state secretary of a politician is included. If no such title is included, this means that the politician is a MP.

4. The political party of the politician(s).

5. The date on which the document has been submitted.

6. Predefined subject(s) relating to the submitted document. The full list of 110 subjects can be found in Table A.1 of Appendix A. Bills do not include subjects, other document do.

7. The type of document. This can mainly either be a motion, amendment, bill, law change, or a modified version of a previously submitted document.

Figure 2.1 and Figure 2.2 show screenshots of a motion and bill, respectively, on OpenKamer.org. As can be seen, the different document types also have different web page formats, this made scraping and pre-processing somewhat more complicated. Pre-processing will be discussed in detail in the next section.

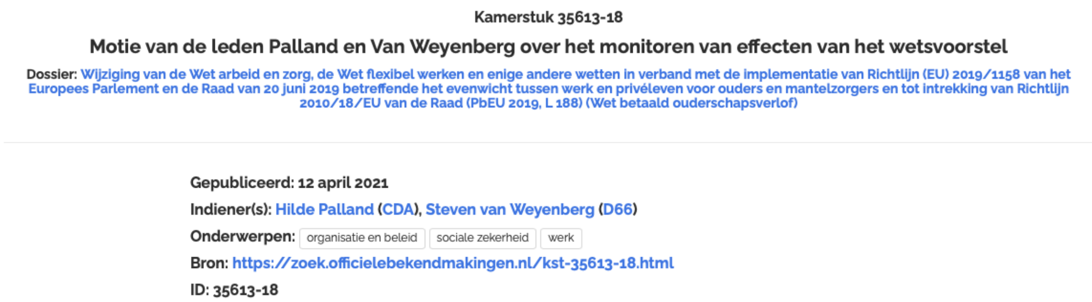

Figure 2.1: Screenshot of the web page of a motion ("motie") on OpenKamer.org. The title, submission date, submitters including political party, and subjects of the motion were scraped from this web page.

Figure 2.2: Screenshot of the web page of a bill ("wetsvoorstel") on OpenKamer.org. The title, submission date, submitter including minister title and political party of the bill were scraped from this web page.

2.1.2 Data Cleaning and Pre-processing

First of all, it should be mentioned that the dataset obtained from OpenKamer.org is not perfect. It sometimes happens that the political party of a politician is not mentioned, if this is the case, this information is obtained at Parlement.com (*Parlement.com*, n.d.) and manually added. Also, the document type is sometimes denoted as the title of the document instead of the type of the document. However, since the title of a document always includes the type of the document, it is relatively easy to convert the title to the actual document type. Also, the dataset included some missing values. In only three cases, no information on any of the variables was available, these three cases were removed. If no information on the submitter(s) were found, these documents were also removed.

One of the pre-processing steps is to remove all the bills and other documents submitted by a minister or state secretary. This means that submissions done by ministers or state secretaries are not included in the final dataset and thus not included in this research. The reason for only including submissions done by MPs is because ministers and state secretaries are not part of the House nor the Parliament but are part of the executive branch of the government. It should be noted that over 89.2% of the bills voted on have been submitted by a minister or state secretary and less than 0.01% of the other document types were submitted by a minister or state secretary. Of the more than 18,000 documents, 1499 documents were excluded from the dataset since these were submitted by a minister or state secretary.

2.1.3 Simple Statistics on the Data

The dataset consists of 16,801 documents over a time period from January 11, 2008 to the July 5, 2022 . The documents are divided into 11,067 motions, 5534 amendments, 191 bills, and 9 other types of documents (e.g. a list of questions and answers).

Furthermore, the dataset is divided into a few time periods. The splits have been made after every Dutch national election. The reason for this is that after every election, the seat distribution in the House changes. The dates are based on the installments of the new MPs. The dataset is split in the following time periods: 30/11/2006-16/06/2010, 17/06/2010-19/09/2012, 20/09/2012-22/03/2017, 23/03/2017-30/03/2021, and 31/03/2021-present.

2.2 Networks

Network Science is a field that connects social and computer science to each other. The basic principle of a network, also called a graph, is that it consists of nodes and edges. Often networks are used in social media to analyse a social network, e.g. Instagram following and followers. Usually, networks are unipartite, this means that all the nodes in the network are of the same type. For example, a node can be an Instagram account and an edge indicates whether one account follows another account. In an unipartite network every node can in theory be tied to every other node, for a bipartite network, this is not possible. In this type of network, contrary to a unipartite network, two different categories of nodes exists and only nodes of the different categories can be connected through an edge.

Figure 2.3 shows a bipartite network of nodes consisting of letters and numbers. As can be seen, there are no edges between the letter nodes, nor are there edges directly connecting the number nodes to one another. Only between the different categories of nodes edges may exist, so only between a letter node and a number node there can be an edge. Figure 2.4 shows the projected network of the number nodes with respect to the letter nodes of the bipartite network in Figure 2.3. Node 1 is connected to node 2 through node A, node 2 is also connected to nodes 3 and 4 through node C, and node 3 is connected to node 4 through node C. The projected network is a unipartite network in which the letter nodes have been removed.

For this research, a bipartite network of submission and submitter nodes was constructed. Edges between the nodes indicate if a MP (co-)submitted a document or not. Only edges between the different node categories are possible, this means that there are no edges between the submissions or between the submitters in the bipartite network. Using a similar approach like Lee et al. (2014), ? (?), Curran et al. (2018), and ? (?) took, the bipartite network is projected to create an unipartite network. This network then consists of MPs only. Here, an edge indicates if two MPs have ever co-submitted a document together, the weight of the edge shows how often they have done so. Multiple edges from one node to other nodes does

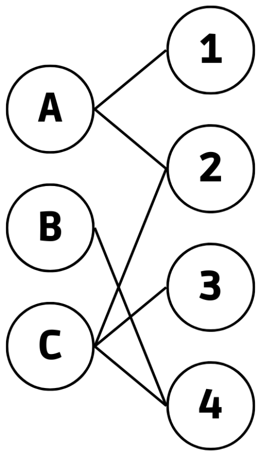

Figure 2.3: A bipartite network of letter and number nodes.

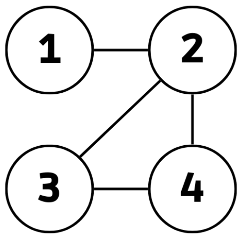

Figure 2.4: The projected network of the number nodes with respect to the letter nodes of the bipartite network in Figure 2.3. This projected network is an unipartite network for which the letter nodes have been removed.

not necessarily indicate how often a MP submits a document together with at least one other MP. Multiple edges can refer to the same submission. In the new unipartite network, the submissions are not included as nodes anymore.

To create the bipartite and unipartite networks, the Python package NetworkX

(*NetworkX — Network Analysis in Python*, n.d.) has been used. As stated on the documentation website of NetworkX, it is a popular Python package for the creation, manipulation, and study of the structure, dynamics, and functions of (complex) networks.

The bipartite network for the period 2021-2022 has been visualized in Figure 2.5. The border of the visualization consists of very small nodes in either green, which are the submitted documents or yellow, which are the MPs. All the edges have the same width, although this does not mean their weights are the same. This bipartite network has 1,405 nodes and 2,792 edges. From this bipartite network, a projection has been done and the unipartite network in Figure 2.6 has been created. As can be seen, there are a lot less nodes in this network, this is because only MPs as nodes are included now. The color of the nodes indicate with how many other MPs a document has been co-submitted, this is the degree of a node. The nodes in the visualization have been ordered by degree. All the edges have the same width so this does not indicate the weight of the edges. It should be noted that the nodes with a degree of zero, meaning it has no edges, are not included in the network. This results in excluding eleven nodes from the unipartite network. The reason for the exclusion is that this research focuses on co-submissions and collaboration by MPs. Having a degree of zero indicates that the MPs has never co-submitted and collaborated on a document, only on their own. The unipartite network has 127 nodes and 1264 edges, this is considerably less than the bipartite network.

2.3 Community detection

A community within a network should consist of nodes and edges that are similar to each other (Fortunato & Hric, 2016). Multiple different community detection techniques exist. For this work, the Louvain method, introduced by Blondel, Guillaume, Lambiotte, and Lefebvre (2008), has been used. This method has been chosen because it has shown to be one of the best performing algorithms for community detection (Harenberg et al., 2014; Hric et al., 2014).

The Louvain method is an efficient algorithm, computationally, especially for large networks. It optimizes modularity via a repeating process. Modularity indicates how much a network is divided into modules, or in this case communities. High modularity indicates clear modules within a network. The modularity score is a number between -1 and 1, with 1 indicating that the communities are completely separate from one another, meaning that there are no edges connecting the different communities. The Louvain approach has a two steps repeating process. Step one only allows local change in communities to optimize modularity. For step two, every community that has been found is turned in one node and a new network

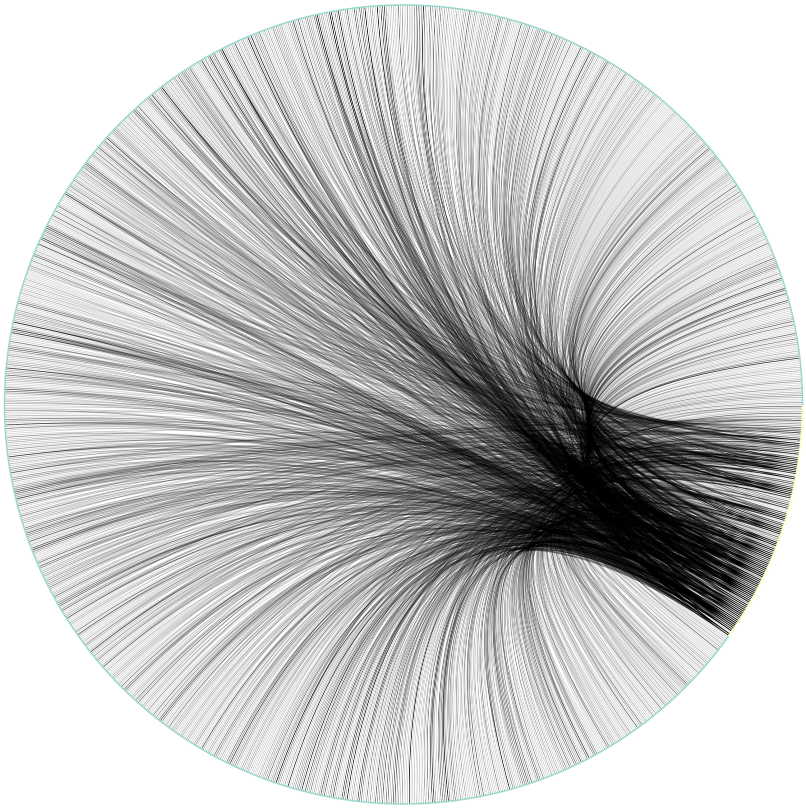

Figure 2.5: Bipartite network for the period 2021-2022. The network includes 1,405 nodes and 2,792 edges.

is build from this. The idea of this algorithm is that it repeats step one and two until modularity cannot be further optimized in step one.

The communities that are detected by the Louvain algorithm are compared to the the political parties of the MPs. This means a comparison between the communities and political parties is made to see whether or not these overlap, and if so, by how much. Also, the modularity score, coverage, and mean F1 score of the network are calculated. The modularity score indicates how much the network is clearly divided into communities. The coverage shows the ratio of edges belonging to a community and the total amount of edges. Lastly, the F1 score is a combination of precision and recall, which are further discussed in the limitations section, which essentially gives an indication of how well communities match with a political party.

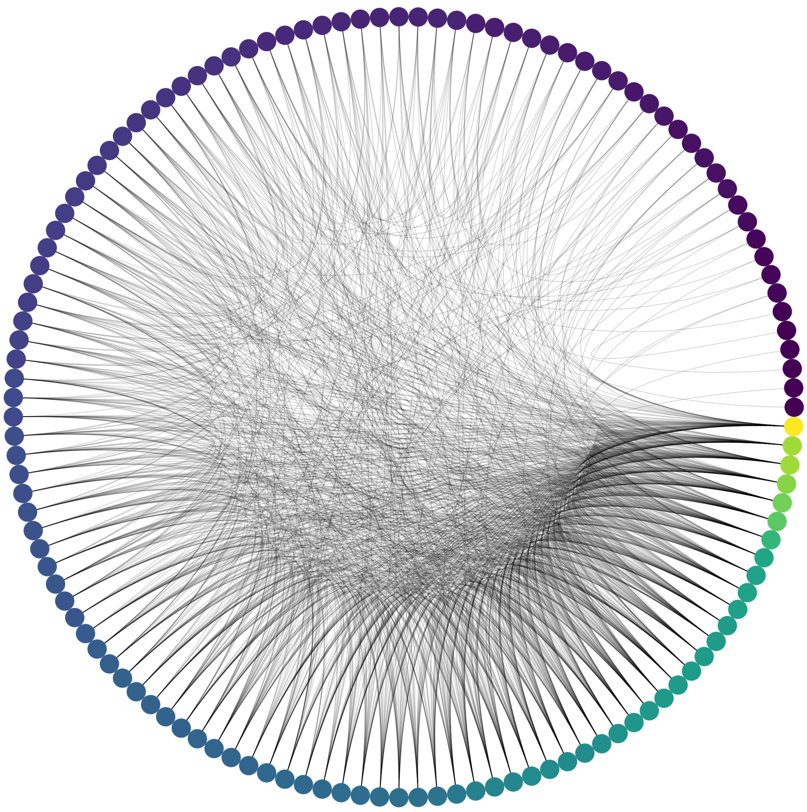

Figure 2.6: Projected network of Figure 2.5 as uniparite network. The network includes 127 nodes and 1,264 edges.

Chapter 3

Results

In this chapter, the results of this research are described. The unipartite network with nodes being MPs and edges indicating co-submissions between MPs for the period 2021-2022 as described in the previous chapter has been used to obtain the results.

Using community detection with the Louvain algorithm on the unipartite network returns five communities with a modularity score of 0.319, coverage of 0.509, and mean F1 score of 0.327. Figure 3.1 shows the unipartite network with the five communities. The colors of the nodes and edges indicate to which community they belong. If an edge has the same color as a node, it means that the edges connects two nodes of the same community, this is an internal edge. The light grey edges between communities indicate that the edge connects two nodes from different communities, this is an external edge.

Position nodes using Fruchterman-Reingold force-directed algorithm.

The algorithm simulates a force-directed representation of the network treating edges as springs holding nodes close, while treating nodes as repelling objects, sometimes called an anti-gravity force. Simulation continues until the positions are close to an equilibrium.

To compare the communities of MPs of the unipartite network in Figure 3.1 to the political parties that the MPs belong to, Figure 3.2 has been created. In this figure, the color of the nodes indicate different political parties. The color of the edges are the same as in Figure 3.1, this means that the colored edges indicate that they belong to a specific community and the light grey edges are external edges. By

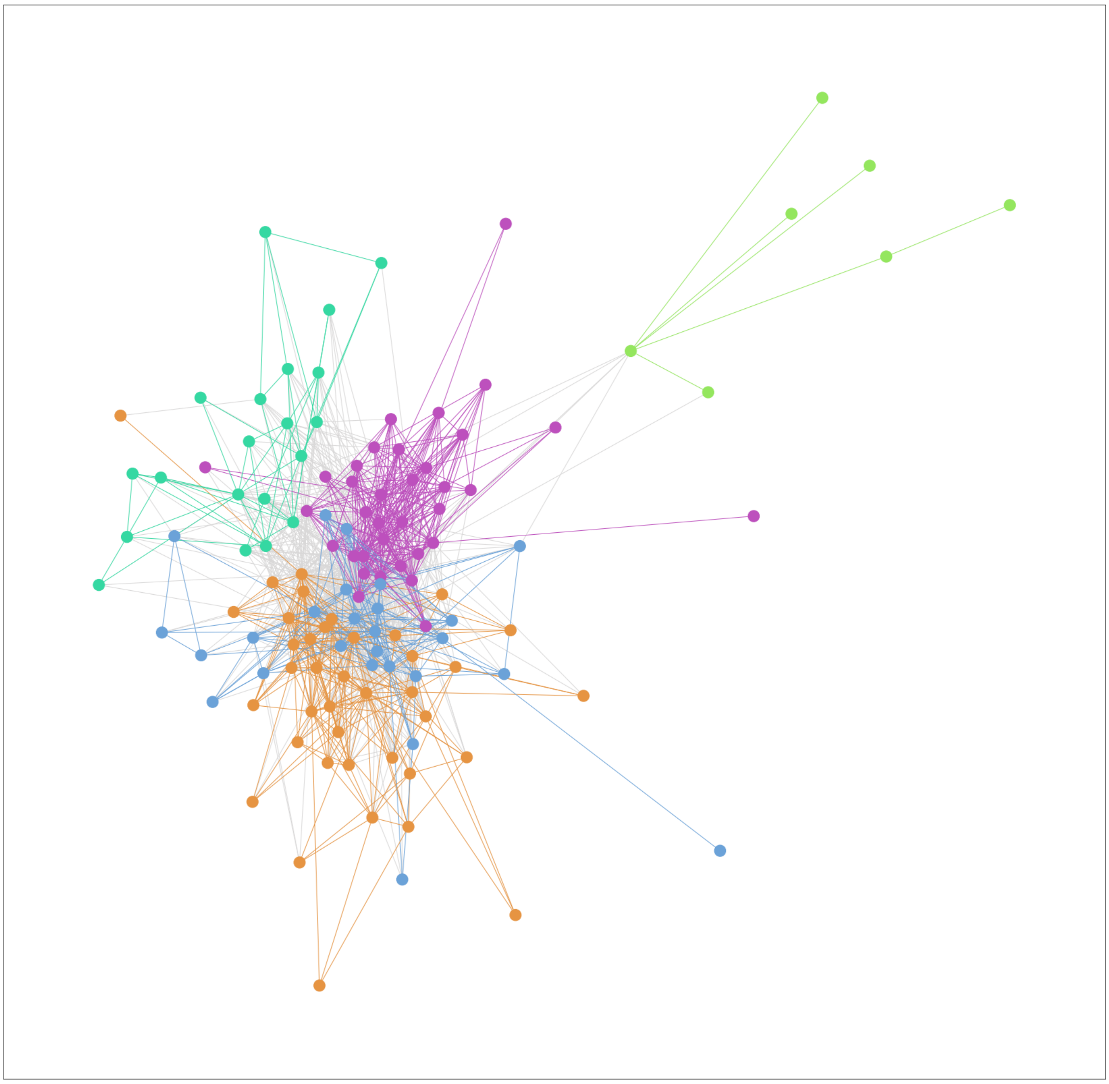

Figure 3.1: The unipartite network for the period 2021-2022 with a force-directed layout. The colors of the nodes and edges indicate to which of the five communities they belong according to the Louvain algorithm. The light grey edges indicate an external edge.

simply looking at the colors of the nodes and edges, it seems like the communities are not similar to the political parties. Only for the top right community in green, it seems like all the nodes belong to the same political party

To further see how the communities compare to the political parties, Figure 3.3 has been created. This figure shows all the political parties with MPs that have at

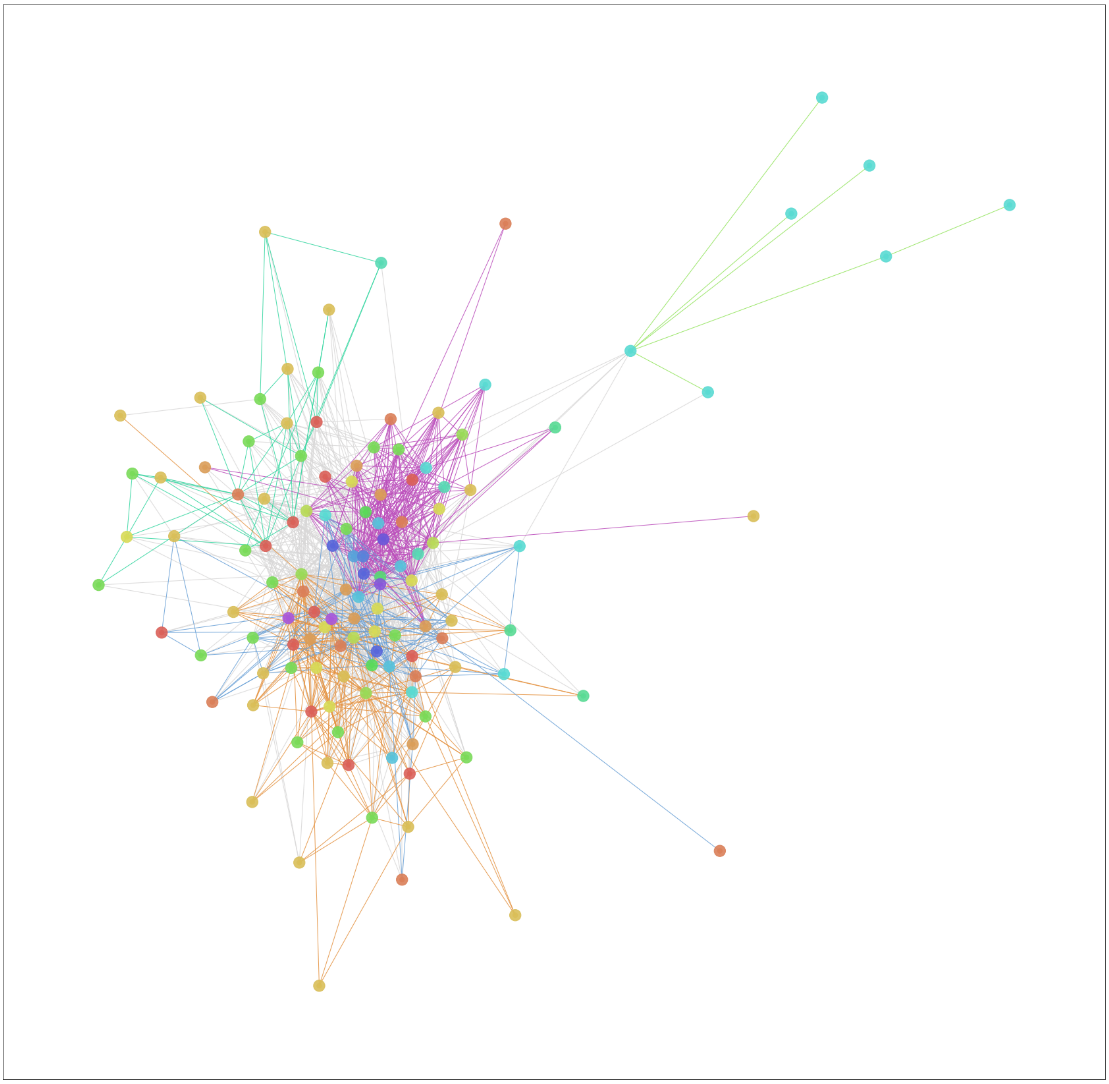

Figure 3.2: The unipartite network for the period 2021-2022 with a force-directed layout. The colors of the nodes indicate different political parties. The colors of the edges indicate the different communities. The light grey edges indicate an external edge.

least submitted one document together with one or more MPs. The bands show how MPs of different political parties are distributed among the five detected communities. The size of the band indicate the number of MPs that belong to a political party or to a certain community. It is very clear that for four of the five communities, there is no one political party that is mainly represented. However, it is interesting to see that community 2 only exists of MPs of the PVV. It is the only community that mainly represents one political party. Nevertheless, not all MPs of the PVV are part of community 2. What is also notable is that community 4 and community 5 both include a relatively big amount of MPs from both the VVD and D66. While community 1 and community 3, and especially community 3, seem to be a more evenly distributed mix of different political parties.

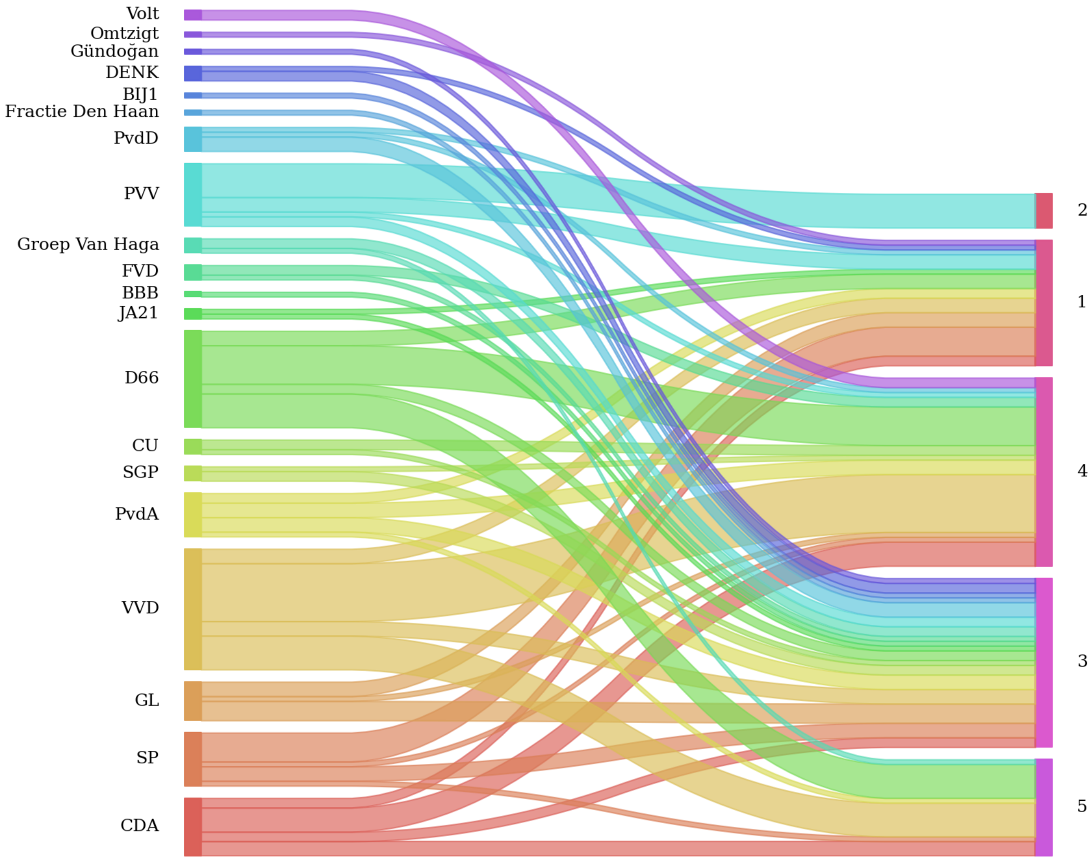

Figure 3.3: A Sankey Diagram that shows the distribtuion of the political parties among the five detected communities by the Louvain algorithm. The size of the bands indicate the number of MPs that belong to a political party or to a certain community.

Chapter 4

Discussion

The goal of this research was to find communities among the co-submissions of MPs and to see whether these communities correspond with the political parties the MPs are a member of.

4.1 Interpretations

Analysing the scores of the community structure mentioned in the results, it shows quite a low modularity score, although it is not negative or zero. A high modularity score would suggest a high division of the unipartite network into communities, a score of around 0.3 suggests a somewhat strong division in the network. The coverage score indicates that around half of the edges in the network are part of a community.

By taking a look at the results, it becomes evident that the communities detected by the Louvain algorithm do not correspond with the political parties. The mean F1 score is rather low which also indicate that the communities and political parties do not match quite well. Only one of the communities consists of MPs of the same political party, but even that political party is distributed over multiple communities. Since the unipartite network that has been created and used for the community detection represents co-submission between MPs, communities consist of MPs that have worked together on a document. It seems reasonable that MPs of different political parties co-submitted a document together, this indicates a support, and thus often votes, by at least two political parties. If a MP co-submits a document with a MP of the same political party, this only shows support of one political party, it might then be harder to convince other political parties to vote in favor of the document. Because of this, it makes sense that the communities do not correspond with the political parties a lot.

4.2 Limitations

In the following paragraphs, the limitations of this research are identified and described. Taking these points into account can improve and deepen this research.

As mentioned before, the dataset used for this research is not perfect. Some information was missing, e.g. the political party of a politician, the title minister or state secretary if this was applicable or the date of a submission. Also, it happened that the title of the document was written as the document type. Lastly, in a few cases it became apparent that the information was not entirely correct, e.g. the wrong submitter was associated with a document. Especially this last point is hard to check. It is virtually impossible to manually (fact) check all the documents. However, if it so happens that a lot of documents include incorrect information, then it makes it very hard to get conclusive results to answer any research question, therefore it can have a big impact on the research. A better quality dataset can help improve future research on this topic.

A suggestion to further check whether a community corresponds with a political party (or any other real life group) and if so, by how much, is to calculate the precision and recall for the communities. Precision and recall are good measures to evaluate community structure with groups in real life (Amigó, Gonzalo, Artiles, & Verdejo, 2009). Precision essentially measures relatively how many nodes in a community have the real life group. For this research, if precision is 1, then this means that all the nodes in a community belong to the same political party. On the other hand, recall would measure how many nodes from one political group end up in the same community. If recall is 1, then all the nodes from a political party are part of the same community. If recall is 0.5, then the nodes of a political party are exactly split among two communities. Using the measures precision and recall, a more detailed comparison between communities and political parties can be performed.

As mentioned in methods chapter, the Louvain algorithm is one of the best performing community detection algorithms. It is very likely that other community detection algorithms provide (slightly) different results. It might be beneficial to compare the results of the Louvain algorithm to other algorithms to see whether any improvements can be found or to confirm that the Louvain algorithm, also for this research's network, is indeed the best community detection algorithm.

Continuing on the previous paragraph, evaluating Louvain's performance can also be done by comparing it to a community detection approach in which the network is split into random communities. By computing a lot of random community structures and calculating the mean precision and recall measures, the scores can be compared to that of the Louvain algorithm. This approach has been done by Cherepnalkoski and Mozetič (2016).

4.3 Future Work

This section provides a number of suggestions to expand this research. Most of the suggestions could be executed using the dataset available for this research. For others, more data should be collected.

First of all, the analysis performed in this research could be expanded to multiple time periods. Other periods have different MPs and a different seat distribution of the political parties, it is very likely the using a community detection algorithm will result in different community structures. It might be interesting to compare the community structures over time periods.

Secondly, this research has only focused on comparing the community structure to the political parties. However, the dataset includes a number of variables for which the community structure could be compared to as well. A few suggestions are: the document types, subjects of the documents, the amount of documents submitted by a MP (over a certain period of time), the number of times a MP co-submits a document, or how often certain MPs work together.

Lastly, similar to the previous paragraph, the community structure can be compared to many other variables. However, for the following variables, more data should be collected. Often, this data is publicly available. In general, communities could also be compared to certain other demographics of MPs. A few examples include their age, gender but also their political career, e.g. whether or not they have been (or will be) a minister or state secretary, if they are the parliamentary group leader (called a 'fractievoorzitter' in Dutch) of their political party, or their seniority in the House, meaning how many days they have been a MP.

Chapter 5

Conclusion

To conclude, this paper focused on the co-submissions by Members of Parliament of different documents in the Dutch House of Representatives by means of a network approach. Data on the different documents including information on the MPs and more has been collected. This data was then used to create bipartite and unipartite networks. Community detection using the Louvain algorithm on the networks could then be performed. After analysing and comparing the detected communities to the political parties of the MPs in different communities, it has become clear that the communities do not correspond to the political parties. However, later research could focus on other aspects of the data that might be more closely associated with the communities. As an example, the predefined subjects of the submitted documents could be compared to the communities.

References

Amigó, E., Gonzalo, J., Artiles, J., & Verdejo, F. (2009, 7). A comparison of extrinsic clustering evaluation metrics based on formal constraints. *Information Retrieval*, *12*(4), 461–486. Retrieved from https://link.springer.com/article/10.1007/s10791-008-9066-8 doi: 10.1007/S10791-008-9066-8/FIGURES/23

Blondel, V., Guillaume, J.-L., Lambiotte, R., & Lefebvre, E. (2008, 3). Fast unfolding of communities in large networks. Retrieved from http://arxiv.org/abs/0803.0476http://dx.doi.org/10.1088/1742-5468/2008/10/P10008 doi: 10.1088/1742-5468/2008/10/P10008

Briatte, F. (2016). Network Patterns of Legislative Collaboration in Twenty Parliaments. *Cambridge Journals*, *4*(2), 266–271. Retrieved from https://halshs.archives-ouvertes.fr/halshs-01363580 doi: 10.1017/nws.2015.31ï

Cherepnalkoski, D., & Mozetič, I. (2016, 12). Retweet networks of the European Parliament: evaluation of the community structure. *Applied Network Science*, *1*(1). doi: 10.1007/s41109-016-0001-4

Curran, B., Higham, K., Ortiz, E., & Filho, D. V. (2018, 6). Look who's talking: Two-mode networks as representations of a topic model of New Zealand parliamentary speeches. *PLoS ONE*, *13*(6). doi: 10.1371/journal.pone.0199072

Fortunato, S., & Hric, D. (2016, 11). Community detection in networks: A user guide. Retrieved from www.opte.org.

Harenberg, S., Bello, G., Gjeltema, L., Ranshous, S., Harlalka, J., Seay, R., ... Samatova, N. (2014, 11). *Community detection in large-scale networks: A survey and empirical evaluation* (Vol. 6) (No. 6). Wiley-Blackwell. doi: 10.1002/wics.1319

Hric, D., Darst, R. K., & Fortunato, S. (2014, 6). Community detection in networks: Structural communities versus ground truth. Retrieved from http://arxiv.org/abs/1406.0146http://dx.doi.org/10.1103/PhysRevE.90.062805 doi: 10.1103/PhysRevE.90.062805

Kim, R. E. (2020, 12). *Is global governance fragmented, polycentric, or complex? The state of the art of the network approach* (Vol. 22) (No. 4). Oxford University Press. doi: 10.1093/isr/viz052

Lee, J.-Y., Jo, H.-J., & Yoon, J. W. (2014, 8). Network Analysis of Korean legislators using Bipartite Network Projection. *Journal of Internet Computing and Services*, *15*(4), 103–110. doi: 10.7472/jksii.2014.15.4.103

Leifeld, P. (2017). Discourse network analysis: policy debates as dynamic networks. In J.N. Victor, M. Lubell, & A.H. Montgomery (Eds.), *The oxford handbook of political networks* (chap. 25). New York, NY, USA: Oxford University Press. Retrieved from http://eprints.gla.ac.uk/121525/

NetworkX — Network Analysis in Python. (n.d.). Retrieved from https://networkx.org/

Open Kamer. (n.d.). Retrieved from https://www.openkamer.org/

Parlement.com. (n.d.). Retrieved from https://www.parlement.com/

Web Scraper. (n.d.). Retrieved from https://webscraper.io/

Yang, S. J., & González-Bailón, S. (2018). Semantic Networks and Applications in Public Opinion Research. In J.N. Victor, A.H. Montgomery, & M. Lubell (Eds.), *The oxford handbook of political networks* (pp. 327–353). New York, NY, USA: Oxford University Press. Retrieved from https://repository.upenn.edu/asc_papers

Appendix A

Predefined Subjects

zorg en gezondheid	dieren
ondernemen	netwerken
economie	religie
organisatie en beleid	overige vormen van onderwijs
koninklijk huis	onderwijs en wetenschap
kunst	industrie
rijksoverheid	bouwnijverheid
bestuur	weg
huren en verhuren	recht
sport	hoger onderwijs
cultuur	ethiek
fiscaal	levensloop
geneesmiddelen en medische hulpmiddelen	sociale zekerheid
bestuursrecht	begroting
burgerlijk recht	belasting
ict	emigratie
defensie	gemeenten
cultuur en recreatie	water
geluid	migratie en integratie
rampen	reizen
kopen en verkopen	gezin en kinderen
bezwaar en klachten	europese zaken
verkeer	parlement
internationaal	strafrecht

handel	militaire missies
integratie	planten
ontslag	transport
toerisme	werkloosheid
jongeren	openbare orde en veiligheid
basisonderwijs	energie
ziekten en behandelingen	tijdelijk verblijf
rechtspraak	landbouw
voortgezet onderwijs	beroepsonderwijs
media	natuur en milieu
arbeidsomstandigheden	bouwen en verbouwen
politie, brandweer en hulpdiensten	financiën
huisvesting	arbeidsvoorwaarden
ziekte en arbeidsongeschiktheid	markttoezicht
gezondheidsrisico's	voedselkwaliteit
de nederlandse antillen en aruba	afval
verzekeringen	staatsrecht
nabestaanden	onderzoek en wetenschap
waterschappen	provincies
waterkeringen en waterbeheer	spoor
ontwikkelingssamenwerking	stoffen
bodem	ruimte en infrastructuur
luchtvaart	internationale samenwerking
lucht	werk
staatsveiligheid	overige economische sectoren
inkomensbeleid	financieel toezicht
nederlanderschap	voeding
terrorisme	natuur- en landschapsbeheer
ouderen	werkgelegenheid
criminaliteit	immigratie
recreatie	ruimtelijke ordening

Table A.1: This table includes all the predefined subjects (in Dutch) that can be associated with a document submitted in the Dutch House of Representatives.

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