Discourse Network Analysis: Policy Debates as Dynamic Networks

Philip Leifeld

Abstract:

Political discourse is the verbal interaction between political actors. Political actors make normative claims about policies conditional on each other. This renders discourse a dynamic network phenomenon. Accordingly, the structure and dynamics of policy debates can be analyzed with a combination of content analysis and dynamic network analysis. After annotating statements of actors in text sources, networks can be created from these structured data, such as congruence or conflict networks at the actor or concept level, affiliation networks of actors and concept stances, and longitudinal versions of these networks. The resulting network data reveal important properties of a debate, such as the structure of advocacy coalitions or discourse coalitions, polarization and consensus formation, and underlying endogenous processes like popularity, reciprocity, or social balance. The added value of discourse network analysis over survey-based policy network research is that policy processes can be analyzed from a longitudinal perspective. Inferential techniques for understanding the micro-level processes governing political discourse are being developed.

Keywords: discourse; network; policy; debate; mixed methods; coalition; content analysis; relational event model; co-occurrence

1 Introduction

Policy debates, or political discourses, are verbal interactions between political actors about a given policy, for example climate or immigration policy. Political actors make public claims about what policy instruments they deem useful and which other measures they reject. Actors participate in policy debates in order to signal their policy platform to voters or potential allies, convince other actors to adopt their ideal points, or reduce their own uncertainty by learning from other actors in the face of technical complexity.

Policy debates can be highly consequential for political outcomes for several reasons: They determine which policies make it onto the parliamentary agenda and which ones are dropped as a result of pre-parliamentary agenda setting; they often determine public opinion, which then feeds back into the domain of political decision making; they also play a role in more private kinds of signaling between actors, for example in discussions and decision making behind closed doors or in bureaucracies; and they have the potential to translate immediate policy outputs into actual outcomes by altering actors' problem perceptions before policies are implemented. Therefore one should care about how political discourse can be measured and, once this goal has been accomplished, how the structure of empirically observable discourses can be explained by looking at their underlying mechanics.

Political actors comprise legislators, interest groups, agencies, parties, and other organizations or individuals who make public statements about an issue. A *statement* is a verbal or written expression of discontent with a policy or in favor of a policy. Statements need to be *public* to qualify as an element of political discourse because only public claims will be instrumental for the goals actors want to pursue in a discourse. For example, a government agency may voice its concerns about the implementability of a certain policy instrument in a parliamentary hearing, or an interest group may suggest that adoption of a specific policy measure would have positive effects on public welfare, in order to assert their interests. Being public can also mean that statements are visible to an intended target audience, but not necessarily to the broader general public. Therefore discourse network analysis is also applicable to politics behind closed doors.

Political discourse is a *network phenomenon* because the statements actors contribute to the discourse are dependent on each other in interesting ways, both temporally and cross-sectionally. In fact, the primary goal of actors is to influence other actors or learn from other actors, which constitutes a relational action. The goal of *discourse network analysis* is therefore to describe the structures of political discourses and infer their generative processes using techniques from the toolbox of network analysis.

This chapter provides an overview of the theoretical roots of discourse networks (Section 2), the coding scheme and variables (Section 3), useful transformations of these data for descriptive discourse network analysis (Section 4), normalization of discourse network data (Section 5), some brief empirical examples (Section 6), a largely non-technical outlook on inferential statistical methods for modeling discourse networks (Section 7), and a brief conclusion that summarizes current research frontiers (Section 8). Although important, this overview does *not* include a discussion of data sources and their validity as these problems are similar in other types of content analysis. Moreover, this overview does not deal with related kinds of semantic network analysis, which are thoroughly discussed by González-Bailón and Yang in Chapter 14 of this Handbook. This chapter rather serves as a primer on descriptive and inferential discourse network analysis from a methodological and theoretical perspective.

The procedures described in this chapter have been implemented in an open-source software called *Discourse Network Analyzer* (Leifeld, 2015) and the R package *rDNA* (Leifeld, 2015). While there are numerous software packages for qualitative content analysis, very few of them have an explicit functionality for exporting network data, especially when the focus is on actors. Database- or spreadsheet-based solutions do not allow the user to revise earlier statement annotations later on. The software *Discourse Network Analyzer* was designed both for the actor-based annotation of statements in text data and for exporting these structured data as networks.

2 Theory

Several relational characteristics of policy debates have been suggested. The most important one is that debates tend to be structured around competing *coalitions*. Several prominent public policy frameworks make explicit reference to coalitions that are formed as a consequence of similar ideas, beliefs, arguments, or policy stances within the same policy domain or subsystem:

The Advocacy Coalition Framework (Sabatier, 1988; Sabatier and Weible, 2007) argues that between two and five “advocacy coalitions” of actors are structured around coherent “policy core policy preferences”, that is, policy instrument preferences. The framework argues that advocacy coalitions are usually stable over decades. Policy learning takes place within rather than between these coalitions, which leads to policy stability. While current applications of this framework often analyze policy coordination, the original formulation placed a stronger emphasis on beliefs and learning as the “glue” of coalitions (Sabatier and Weible, 2007).

Argumentative Discourse Analysis (Hajer, 1993, 1995) asserts that conflict over environmental and other policy issues is structured by “discourse coalitions”. They primarily serve to defend or propose coherent arguments and narratives as justifications for policy proposals. In this regard, the main difference between advocacy coalitions and discourse coalitions is that advocacy coalitions deal with multiple issues and actors' stances on them while discourse coalitions are concerned with only one issue at a time but multiple justifications for a positive versus a negative stance on the issue. If discourse network analysis operationalizes advocacy coalitions by coding statements on different policy instruments, one can therefore expect multiple complex coalitions with different topical foci, while coding arguments for or against a specific issue as an operationalization of discourse coalitions would rather lead to two distinct coalitions and thus a certain degree of bipolarization by design.

Other policy frameworks and theories make implicit reference to the idea of coalitions. For example, Punctuated Equilibrium Theory (Baumgartner and Jones 1991), the literature on "policy paradigms" and social learning (Hall 1993), and the notion of epistemic communities (Haas 1992; Roth and Bourgine, 2005) all deal with groups of actors who share similar beliefs.

The existence of coalitions is an expression of cross-sectional clustering of actors around similar statements. Analyzing the co-presence of coalitions in a system of actors permits an evaluation of the overall level of cooperation and conflict within the system and therefore effectively reveals the degree of polarization of actors in the system.

Besides cross-sectional clustering, the policy process and public opinion literature has argued that temporal clustering of topics is at work. Downs (1972) suggests that there is a competition between different issues for attention ("up and down with ecology"). Issues go through an "issue attention cycle" because novel discoveries are valued higher by public opinion than known policy problems. The consequence is that actors seek to "acquire power in part by trying to influence the political discourse of their day" (Hall, 1993: 290) by jumping on the bandwagon and discussing currently popular topics. Similarly, the notion of "political waves" (Wolfsfeld, 2001; Wolfsfeld and Sheafer, 2006) rests on the observation that actors compete for attention in the news. Due to changing topics in the news media (or other public venues), they have to adapt to changing topics. In other words, discussion topics come and go over time, effectively leading to a temporal clustering of statements.

There are two distinct levels that are frequently analyzed in relational studies of political discourse: the configuration of actors and the structure of the contents of a debate. While coalitions may be observed at the actor level, the equivalent of clusters of ideas, policy preferences, beliefs, or justifications at the content level is often termed a "frame" (Goffman, 1974; Rein and Schön, 1993). Frames are composed of "concepts", which is a neutral word for policy beliefs, preferences, justifications etc. at the content level. A frame can be defined as a congruent set of concepts, where congruence derives from common usage by the same actors and therefore ideological and intrinsic compatibility (Roth and Bourgine, 2005). According to Steensland (2008: 1030), "few existing studies link frames with the actors who sponsor them, thus presenting an oddly disembodied picture of framing processes." A relationally explicit treatment as in discourse network analysis allows such a joint analysis.

Besides coalition formation (clustering at the actor level), framing (clustering at the level of concepts), and issue attention cycles (temporal clustering of statements), other theoretical mechanisms may guide the development of policy debates. Much abstract theorizing exists and often goes back to classic works in political or social theory such as Critical Discourse Analysis and Deliberative Democracy (Foucault, 1991; Habermas, 1981), which paved the way for relating language and verbal interaction to the notion of power. Yet, few systematic, empirical, replicable accounts of how these mechanisms shape policy debates as complex systems can be found in print. Discourse network analysis permits studying these mechanisms in such a systematic way in order to facilitate theory building with regard to policy debates.

3 Coding scheme and variables

Empirical discourse network analysis is based on a combination of category-based content analysis and network analysis. During the first step, text data are annotated using a coding scheme that is amenable to network analysis. Depending on the type of debate to be analyzed, useful text sources may be newspaper articles, parliamentary testimony, or other types of documents.

Within each document, statements are annotated. They are the basic unit of analysis. A statement may consist of four variables, but this definition can be adjusted to the research purpose or theory:

First, the *actor* $a \in A = \{a_1, a_2, \ldots, a_m\}$ is the person or organization who speaks. Most theories related to the policy process and policy networks assume that organizations are the primary actors in the policy process, and for theoretical clarity, the decision which kind of actor is analyzed—persons or organizations— should be made before the analysis is conducted.

Second, the *concept* $c \in C = \{c_1, c_2, \ldots, c_n\}$ is an abstract representation of the contents that are discussed. If advocacy coalitions are operationalized, concepts are claims for policy instruments. For example, in the debate on what to do about climate change, concepts could be "we should adopt cap and trade" or "we should replace coal and gas by nuclear power". In contrast, if discourse coalitions in the sense of Hajer (1995) or political claims (Koopmans 1996; Koopmans and Statham, 1999) are operationalized, concepts would rather be justifications or narratives. For example, in the debate on whether nuclear energy should be promoted, concepts could be justifications revolving around "health" or "jobs": some actors may argue that nuclear energy is preferable because it causes fewer cases of lung cancer close to the plant, and other actors may argue that its share should not be increased because it causes more cases of cancer in general due to radiation. In both cases, actors speak about the concept of "health" to justify their position on nuclear energy. When justifications or narratives are used, one can expect by design that two opposing coalitions emerge. The question then becomes to what extent each coalition argues in a coherent way (that is, whether different actors use the same set of concepts and whether that pattern is consistent over time) and how polarized the coalitions are (that is, is there a certain extent of common ground or not?). When policy instruments are used and thus a more encompassing analysis is conducted, one can usually expect more diversity even within groups, and more than two coalitions are possible. For example, in the debate on old-age security, there could be a coalition favoring various privatization measures, another one favoring fertility-inducing policy instruments, and another one calling for various labor market instruments; depending on the case, there may be more or less overlap between these coalitions.

The third variable in each statement consists of the *agreement* relation $r \in R = \{r_1, r_2, \ldots, r_l\}$. It acts as an edge qualifier and is usually a dichotomous variable (that is, $l = 2$), which captures the sentiment of the statement. It is said to be "positive" (r_1) if the actor refers to the concept in an affirmatory way and "negative" (r_2) if the actor rejects the concept or uses a negative connotation. In the previous example about nuclear power justifications, the first statement was positive and the second one was negative. The distinction between positive and negative statements is important because competing coalitions may refer to the same concepts in the debate, but with different stances. Ignoring agreement or disagreement and using only "topics" (as is frequently done in other approaches) would connect nodes from competing coalitions, and they would eventually end up in the same coalition despite having opposite opinions. When policy processes are analyzed, it is therefore crucial to move beyond establishing similarity by joint topic affiliation.

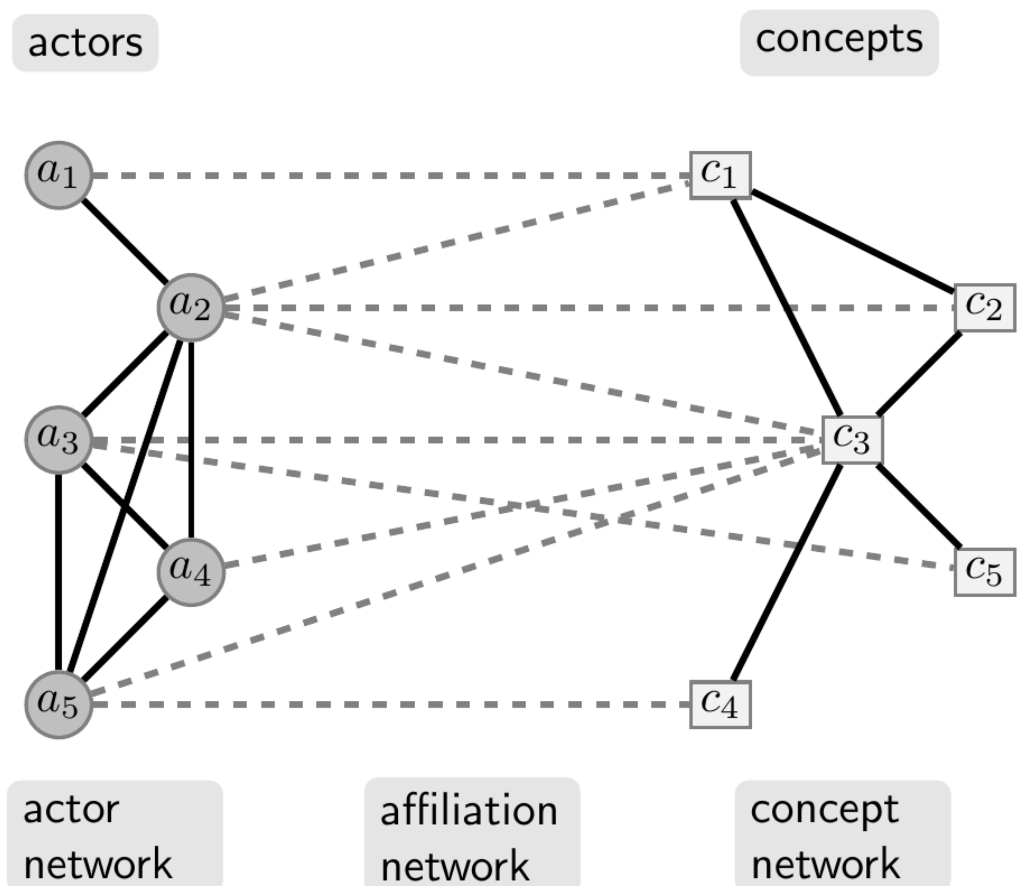
Fourth, each statement carries a time or date stamp, for example the day on which the statement is made. This allows for the temporal analysis of policy debates. Time is actually continuous, but for the sake of simplicity it will be modeled as discrete in the first couple of steps before introducing dynamic methods that make use of time as a continuous variable. Therefore $T = \{t_1, t_2, \ldots, t_k\}$ denotes the set of discrete time steps, for example the set of months or years in which statements are made.

The coding scheme can be adjusted to the problem or theory at hand. For example, the narrative policy framework (Jones and McBeth, 2010; Shanahan, Jones, and McBeth, 2011) requires coding other variables like villains and heroes, and political claims analysis (Koopmans, 1996; Koopmans and Statham, 1999) requires variables like addressee, tone, and location. In these cases or yet other frameworks, the descriptive network models below can be adapted accordingly.

4 The descriptive network model

Discourse network analysis can be descriptive or inferential. If the goal is to trace a debate over time, visualize competing coalitions, and analyze their characteristics, this can be achieved by employing several descriptive network analysis methods. In particular, six simple transformations of the data are useful for exploring policy debates: an *affiliation* network, an *actor congruence* network, an *actor conflict* network, a *concept* congruence network, a *time window* network, and an *attenuation* network.

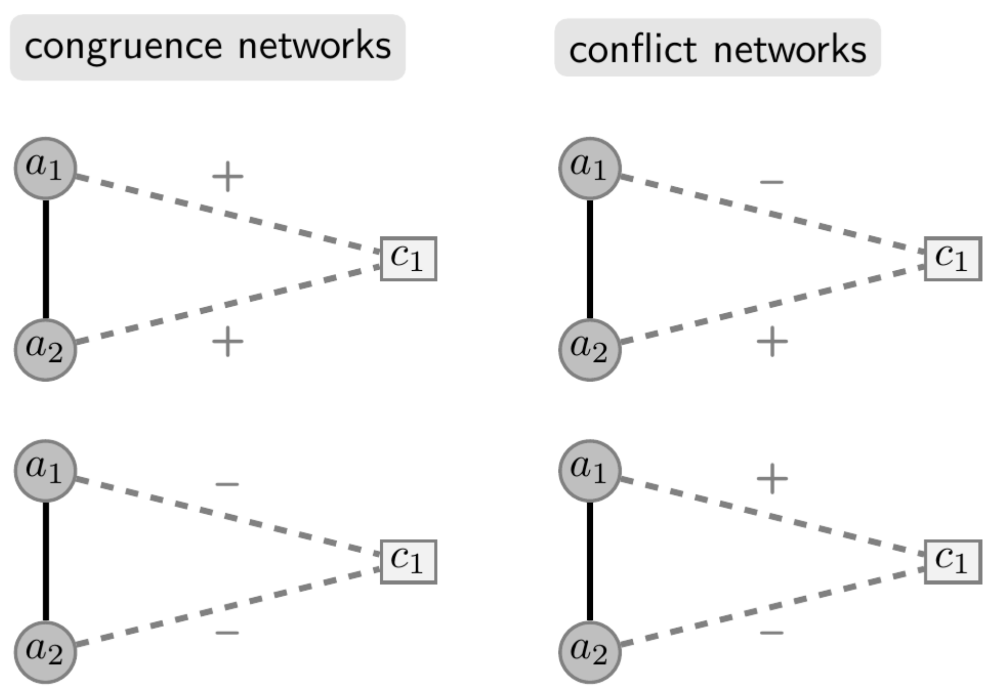
Figure 1: Simple transformations for descriptive discourse network analysis. Simplified illustration without agreement relation. Actor–concept statements (= affiliation networks) can be inferred directly from text data. Actor networks and concept networks can be created from the affiliation network by means of co-occurrences. Source: Janning et al. (2009) and Leifeld (2016).



The first step is to create an affiliation network (= two-mode network or bipartite graph) $G_{r,t}^{aff} = (A, C, E_{r,t}^{aff})$ from the statements that have been annotated in the text. In this notation, a *statement* can be understood as an edge from an actor to a concept at a specific point in time in a positive or negative way, in short $e_{r,t}^{aff}(a, c) \in E_{r,t}^{aff}$, where $E_{r,t}^{aff}$ denotes the set of edges in relation r and time slice t. In

Figure 1 (cf. Janning et al. 2009), a simplified illustration without any agreement relation, edges are the dashed gray ties in the middle that connect actors to the concepts they are employing. Note that two separate affiliation networks can be computed: one for positive mentions of concepts and one for negative ones. Each affiliation network usually contains only binary ties within a time step because the rate at which an actor uses the same concept rarely contains any useful and unbiased information, for example because journalists decide how often an interview partner is asked to report his or her opinion. The profile of ties, that is, which concepts the actor evaluates positively, which ones negatively, and which ones not at all, is usually more important and less biased by external factors than the frequency of each statement. The positive and negative affiliation networks can also be combined into a signed network and visualized with different edge colors, for example green for agreement and red for rejection. It is possible to define t as the whole time range of a discourse or look at consecutive time slices (e. g., years) separately by setting t accordingly. This allows the user to explore which actors adopt what issue stances and how this changes over time.

Figure 2: Different types of actor networks. Either congruence or conflict networks can be created from affiliation networks, depending on how the agreement qualifier is used to aggregate the one-mode network.



However, such a two-mode analysis does not tap the full potential of network analysis. In particular, the visualization may quickly become too complex to infer any systematic meaning from it.

Moreover, a more direct operationalization of coalitions would be desirable. For this reason, one can compute one-mode projections $G_t^a = (A, E_t^a)$ of the affiliation network that preserve the information stored in the agreement variable. Consider the solid lines in Figure 1 on the left: whenever two actors refer to the same concept, they are directly linked in this co-occurrence network. The weight of the edge between two actors is proportional to the number of different concepts both actors refer to. There are two different ways that one can aggregate ties in the actor network (see Figure 2): in a congruence network, a tie is established (or its edge weight is increased by 1) every time two actors refer to the same concept both in a positive way or both in a negative way. The edge weight in an actor congruence network is therefore given by

$$w_t(a, a') = \sum_{r=1}^{l} |N_{G_{r,t}^{aff}}(a) \cap N_{G_{r,t}^{aff}}(a')|$$

where $N_{G_{r,t}^{aff}}(a)$ denotes the neighboring nodes of a in the affiliation graph, that is, the concepts used by a, and the vertical bars denote the cardinality of the set. In other words, the similarity between actors a and a' is defined as the number of concept-stances both actors have in common. This definition captures concept agreement between the two actors and prevents actors from ending up in the same coalition just because they are attached to the same concepts but with opposite stances. Actor congruence networks capture important properties of policy debates in an intuitive way. For example, cohesive subgroups in the actor congruence network are a straightforward operationalization of advocacy or discourse coalitions. They can be identified using graph-theoretic community detection algorithms such as community detection based on edge betweenness (Girvan and Newman, 2002), modularity maximization (Newman and Girvan, 2004; Newman, 2006), or other techniques suitable for identifying subgroups in networks. Clusters in the actor congruence network are groups of actors with similar profiles of opinions.

Similarly, one can create a conflict network, where a tie is established (or its weight is increased) if both actors have opposing agreement patterns (see Figure 2 on the right). Substantively, this results in a network with negative ties (Labianca and Brass, 2006). The value of an edge indicates the intensity of conflict between two actors. This can be interesting because a congruence network only captures agreement whereas disagreement must be inferred from the absence of edges. This may be insufficient in some cases because it is not possible to distinguish between absent edges due to disagreement and absent edges due to the fact that some actors do not reveal their preferences. Edge weights in the conflict network can be expressed in a similar way as in the congruence network:

$$w_t(a,a') = \left|N_{G^{aff}_{r=1,t}}(a) \cap N_{G^{aff}_{r=2,t}}(a')\right| + \left|N_{G^{aff}_{r=2,t}}(a) \cap N_{G^{aff}_{r=1,t}}(a')\right|$$

where the edge weight is the number of concepts actor a agrees on and the other actor a' disagrees on, or vice-versa. In the resulting graph, two actors are connected if they have opposing views, and their edge weight indicates the strength of disagreement between them.

One may be tempted to apply the same transformations to the concept level in order to identify frames or ideologies in terms of joint usage by actors. However, this is slightly more complicated because the direction of agreement may differ across concepts. For example, (positive) agreement to nuclear power in order to curb emissions may be related to (negative) disagreement with subsidies for coal and gas, but it may be at the same time related to (positive) agreement to higher regulatory standards with regard to emissions. In other words, relating concepts only when both of them are used in the same way would be useless because some concepts are inherently formulated in a reversed way. To rectify the problem, it is possible to redefine each concept node to be intrinsically linked to one of the agreement patterns: $c^* \in C^* = \{c_1^{r=1}, \dots, c_1^{r=l}, c_2^{r=1}, \dots, c_2^{r=l}, \dots, c_n^{r=1}, \dots, c_n^{r=l}\}$. This yields twice as many concepts as before (if $l = 2$). For example, the node set for concepts would consist of items like "cap and trade—yes" as well as "cap and trade—no" and similar positive and negative pairs of concepts. The agreement qualifier would then no longer matter for the construction of the network. In that case, congruence can be expressed as follows.

$$w_t(c^*, c^{*\prime}) = |N_{G_t^{aff}}(c^*) \cap N_{G_t^{aff}}(c^{*\prime})|$$

In other words, the more actors use two concept–agreement tuples jointly in the same time period, the greater the similarity between these two items. This is an indicator of ideological fit between the two signed concepts because they need to be compatible in order to be usable by the same person or organization. Just like the whole congruence network provides an operationalization of coalitions as densely interconnected subgroups, clusters in the concept congruence network can be interpreted as frames or ideologies.

For all of these transformations, it is possible to create versions that take into account the time axis more explicitly. At least two different kinds of transformations may be useful. One of them is based on a time window. The idea is that the meaning of concepts may change over time. If an actor speaks in favor of higher emission standards in a given year, and another actor proposes higher emission standards twelve years later after the standards have in fact been altered in the meantime, should these two actors be connected? The time window approach corrects for this changing context by establishing congruence or conflict ties only within a certain time window of a pre-specified number of days. The time window is then moved forward along the time axis, and ties or weights are added to the existing network within each time step. This effectively corrects for problems with changing contexts, and it imposes a temporal restriction in the sense that similarity derives from temporally local interactions.

Yet, this method effectively applies a discrete function to time. The weight is added to the network if interaction between two nodes takes place within the time window, and it is not added at all if the interaction spans only one day more than the length of the time window. One may prefer to impose a continuous time function such that the longer ago the first actor made the same statement, the less a second actor's identical statement at the current time point matters for the edge weight. In such an "attenuation network", edge weights that are added to the network can be weighted by arbitrary functional forms of the number of days that have passed between the two statements, most commonly an exponential decay function with a decay parameter provided by the user. An attenuation network thus values temporally local interactions within a few days much higher than congruence or conflict over long time periods. This also makes sense from a conversation perspective because actors are much more likely to respond to other claims in a debate within a few days.

In principle, either the time window approach or the attenuation approach can be used to create dynamic visualizations of how policy debates and their coalitions and polarization change over time. More details about these time algorithms including dynamic visualization are provided by Leifeld (2013, 2016).

All of the transformations suggested above have their own strengths and weaknesses. Affiliation networks serve to view the full set of information but may be too complex for meaningful interpretation by means of visual inspection; congruence networks are intuitive operationalizations of coalitions and frames, respectively, but normalization methods may have to be applied due to different levels of activity and diversity of actors (see next section); conflict networks offer a direct operationalization of actor conflict but is harder to interpret visually; and temporal transformations like the time window approach and the attenuation method serve to correct the actor congruence network by admitting only temporally local interactions. As a starting point for exploring an empirical debate, normalized actor congruence networks and affiliation networks may be the easiest and most intuitive options.

5 Normalization of discourse networks

In most congruence networks, it is important to normalize edge weights. Consider the actor congruence network depicted in the upper panel of Figure 3. The example shows the German policy debate on the future of the pension system during the first six months of the year 2000. The different node colors indicate actor types. Gray nodes—government actors and political parties—are located at the center of the network. The hyperplanes represent coalitions as identified by edge betweenness community detection (Girvan and Newman, 2002) implemented in the visualization software visone (Brandes and Wagner, 2004). Clearly, government actors and parties are most central due to their large numbers of statements. This is a typical pattern across many kinds of discourses: some actors are more mediagenic than others because they are officially in charge of a problem (e. g., the Ministry of Social Affairs is in charge of dealing with pension politics), and some actors follow a membership logic according to which they are by definition more diverse than others with regard to opinions (e. g., political parties often have multiple party wings). Their activity and diversity causes these actors to have agreement ties to most other actors in the network at some point. The result is a core–periphery structure where coalitions cannot be easily identified. Is this an artifact because discursive similarity is confounded by institutional roles of actors, or is this a feature rather than a bug? Both perspectives are defensible, but if the goal is to find coalitions based on the similarity of actors' policy preferences, one may prefer to abate this nuisance.

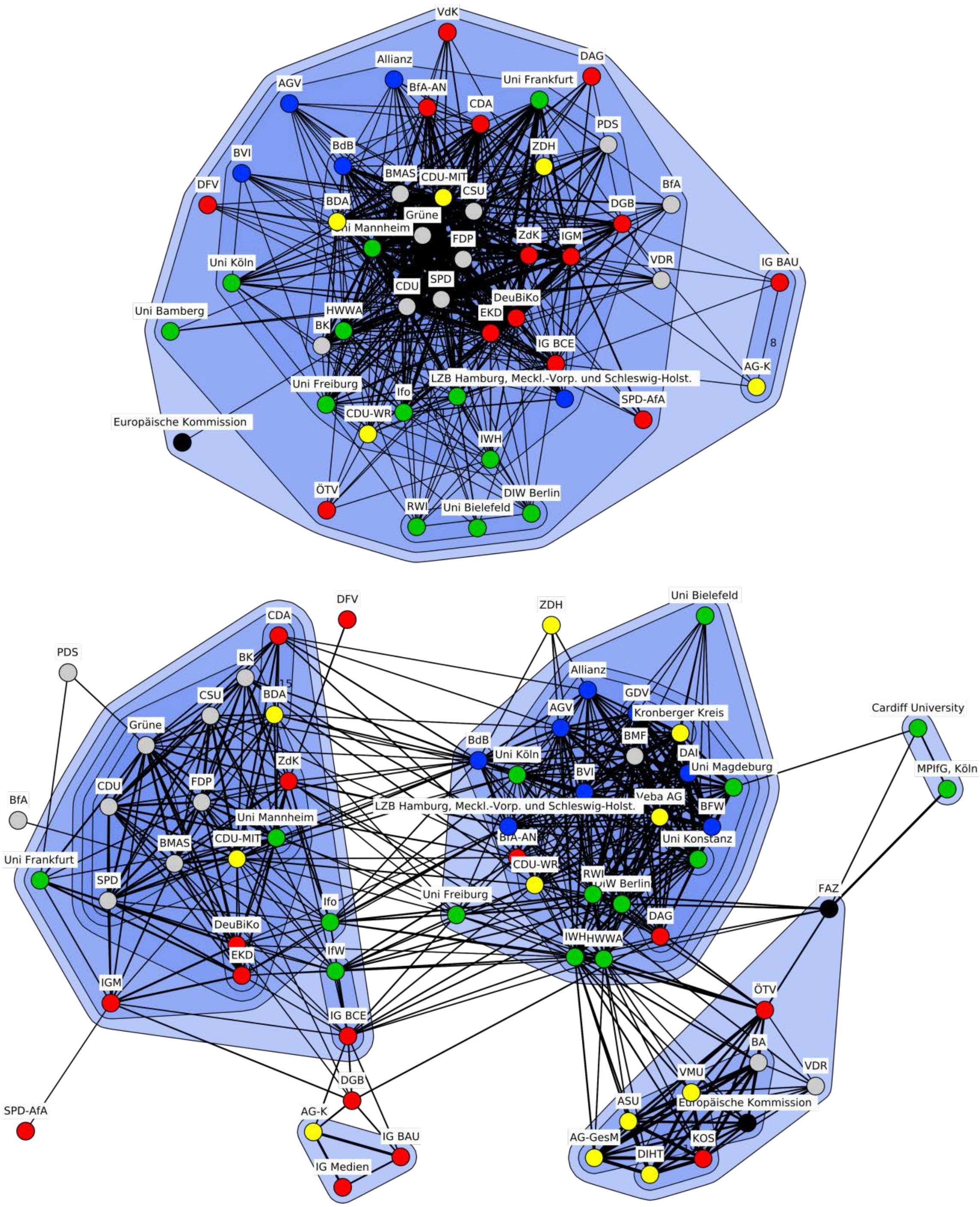
There are several types of normalization that can be applied to an actor congruence network in order to correct for this "institutional bias". A simple and effective method is to divide each edge weight by the average number of different concepts the two actors use (either in a positive or negative way):

$$\Phi(w_t(a,a')) = \frac{\sum_{r=1}^{l} |N_{G_{r,t}^{aff}}(a) \cap N_{G_{r,t}^{aff}}(a')|}{\frac{1}{2}\left|N_{G_{r=1,t}^{aff}}(a) \cup N_{G_{r=2,t}^{aff}}(a)\right| + \left|N_{G_{r=1,t}^{aff}}(a') \cup N_{G_{r=2,t}^{aff}}(a')\right|}$$

For the pension example network, this normalization results in the network shown in the lower panel of Figure 3. It is easy to see that several distinct coalitions can be identified now.

Two other kinds of normalization are able to minimize this bias. Both are based on vector similarities. Rather than a co-occurrence approach as presented above, one can formulate the concept profile of an actor as a vector $\vec{a}$ of length $|C^*|$ with entries 0 (indicating no statement about a concept–agreement tuple) and 1 (indicating affiliation with a concept–agreement tuple) at a given time step and then compute the similarity between the concept vectors of two actors. At least two similarity measures are known to have normalizing properties when some entries have zeros (Leydesdorff, 2008), a situation that is equivalent to having vectors with unequal lengths. The first one is the Jaccard similarity measure:

Figure 3: Normalization. An example from German pension politics, January to June 2000. Blue hyperplanes are the result of an edge betweenness community detection algorithm; edges width reflects the extent of actor congruence via shared concept stances; gray nodes are political parties and government actors; blue nodes are financial market actors; green nodes are scientific organizations; red nodes are trade unions or social interest groups; yellow nodes are employers' associations. Upper panel: If there are actors with diverse opinions and a high statement activity (here: the state actors and parties at the center) and if the actor congruence network is not normalized, a core–periphery structure emerges. Lower panel: Same network as before, but with normalization. If all edge weights are divided by the average number of different concepts employed by the two actors involved in an edge, the core–periphery structure vanishes, and the coalition structure becomes visible.



$$w_J(a,a') = 1 - \frac{M_{11}}{M_{01} + M_{10} + M_{11}}$$

where M_{11} denotes the number of concepts where both actors have a 1, and M_{01} and M_{10} are the numbers of concepts where only the first respectively the second actor has a 1. The second measure with normalizing properties is known as cosine similarity:

$$w_C(a,a') = \frac{\sum_{i=1}^{n} \vec{a}_i \, \vec{a}'_i}{\sqrt{\sum_{i=1}^{n} (\vec{a}_i)^2} \cdot \sqrt{\sum_{i=1}^{n} (\vec{a}'_i)^2}}$$

which is equivalent to dividing the edge weights of the actor congruence network by the square root of the product of the degree centralities of both incident nodes across positive and negative statements (Newman 2011: 26; compare for the first normalization measure suggested above):

$$\Phi(w_t(a,a')) = \frac{\sum_{r=1}^{l} |N_{G_{r,t}^{aff}}(a) \cap N_{G_{r,t}^{aff}}(a')|}{\sqrt{\left|N_{G_{r=1,t}^{aff}}(a) \cup N_{G_{r=2,t}^{aff}}(a)\right| \cdot \left|N_{G_{r=1,t}^{aff}}(a') \cup N_{G_{r=2,t}^{aff}}(a')\right|}}$$

Both metrics, Jaccard similarity and cosine similarity, are standardized between 0 and 1. Beside normalization purposes, these vector similarities can also be fed into hierarchical cluster analyses, non-metric multidimensional scaling, or other clustering techniques that are based on distance or similarity measures in order to identify coalitions in a policy debate as an alternative to community detection in the congruence network.

A fourth normalization measure, the *subtract* method, tackles the problem that actor congruence networks only consider congruence ties, but not conflict. There may be cases where two coalitions have substantial conflict with regard to some concepts and also substantial agreement on other concepts. A congruence network would only consider the agreement patterns and wrongly identify a single coalition. A simple solution to this problem is to compute both a congruence network and a conflict network and then subtract the conflict edge weights from the corresponding congruence edge weights. The result is a signed, weighted network where positive ties represent agreement in excess of conflict and where negative ties indicate more conflict than congruence. As in any of the other network types, one can subsequently impose threshold values on the edge weights in order to remove low-intensity (or in this case: negative) ties for purposes of visualizing the network. This will correct the congruence network by removing the bias that may arise because conflict ties are ignored when the congruence network is created. Moreover, if positive and negative usages of concepts have similar frequencies, this type of normalization will effectively remove the institutional bias reported above. For an application, see Nagel (2015).

6 Brief descriptive examples

Discourse network analysis has been applied to several policy sectors like pension politics (Leifeld, 2013; 2016), climate politics (Fisher, Leifeld and Iwaki, 2013; Fisher, Waggle and Leifeld, 2013; Broadbent and Vaughter, 2014, Gkiouzepas and Botetzagias, 2015; Schneider and Ollmann, 2013; Stoddart and Tindall, 2015; Wagner and Payne 2015; Yun et al., 2014), software patents and property rights (Leifeld and Haunss, 2012; Herweg, 2013), internet policy (Breindl 2013), infrastructure projects (Nagel, 2015), energy policy (Brutschin, 2013; Haunss, Dietz, and Nullmeier, 2013; Mayer, 2015; Rinscheid, 2015; Rinscheid et al., 2015), shooting rampages (Hurka and Nebel, 2013), abortion (Muller, 2014a, 2014b, 2015), outdoor sports (Stoddart, Ramos and Tindall 2015), water politics (Brandenberger et al., 2015; Cisneros 2015), deforestation (Rantala and Di Gregorio, 2014), genetically modified organisms (Tosun and Schaub 2015), higher education (Nägler 2015), and online deception (Wu and Zhou, 2015), among others.

A simple example of German pension politics between 1993 and 2001 based on newspaper articles shall illustrate the use of descriptive discourse network analysis. Details about data collection and the study design can be found in Leifeld (2013; 2016). The study examines the use of 68 different solution concepts for fixing the old-age pension system in the face of financial problems and population aging. 246 organizations made 7,249 positive or negative statements about these concepts in a newspaper over the course of nine years, culminating in a major policy reform. The new law was adopted in 2001 and introduced privatization measures although the 68 distinct solution concepts had very different substantive foci, ranging from privatization over labor-market policy instruments to fertility incentives. What dynamics led to the narrowing down of the set of politically feasible concepts? The literature on pension politics argues that there was a single policy coalition until the mid-1990s and an erosion of this cohesive group of actors and concepts took place between then and 2001 (see Leifeld, 2013 and 2016 for details). The research question is therefore: How is this policy change predated by changing coalitions in the policy debate?

To answer this question, Leifeld (2013; 2016) computes annual time slices of normalized actor congruence networks for the complete years of 1997, 1998 and 2000 and the five months leading up to the reform in 2001, respectively. Edges with a weight lower than a certain threshold value are removed for clarity. This threshold value for filtering out less intense edges is set individually for each network. The cutoff values are only necessary for easier visual interpretation of the network diagrams. These procedures lead to several consecutive network visualizations similar to the lower panel in Figure 3. The actual figures can be found in Leifeld (2013). The analysis of the development of coalitions over time reveals a strong pattern from one dominant corporatist coalition over a strong bipolarization of two coalitions, some actors leaving the previous coalition and joining the opponent, to an erosion of the corporatist coalition and institutionalization of the new coalition that revolves around privatization ideas. In this case study, the discourse network analysis is able to derive in detail when and how these changes came about.

Figure 4: Threshold values. Whole time period from 1993 to 2001 in the German pension policy debate. Actor congruence network with varying threshold values. With decreasing cutoff levels, more details are visible, but the coalition structure is harder to identify. Source: Leifeld (2016).

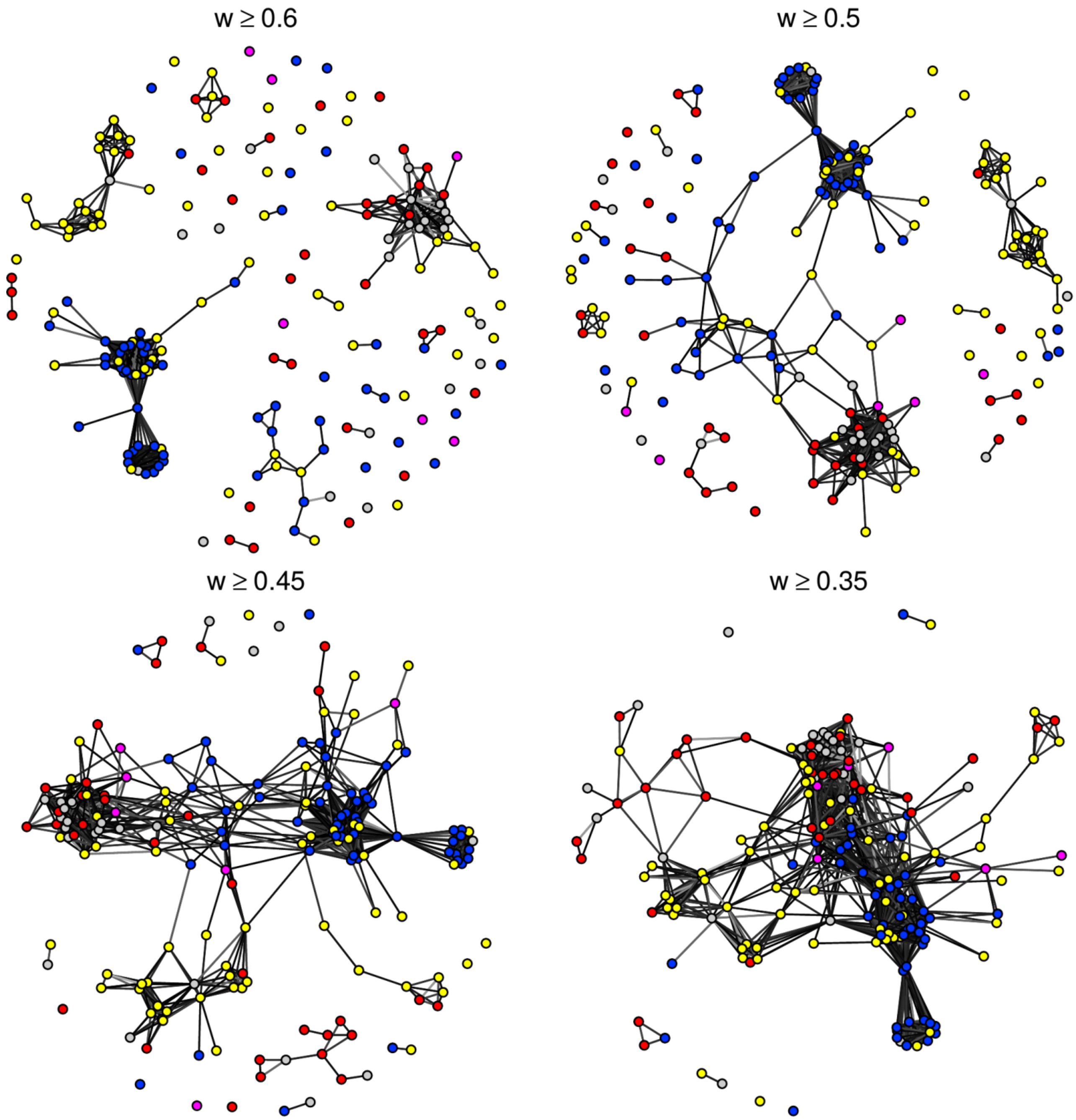
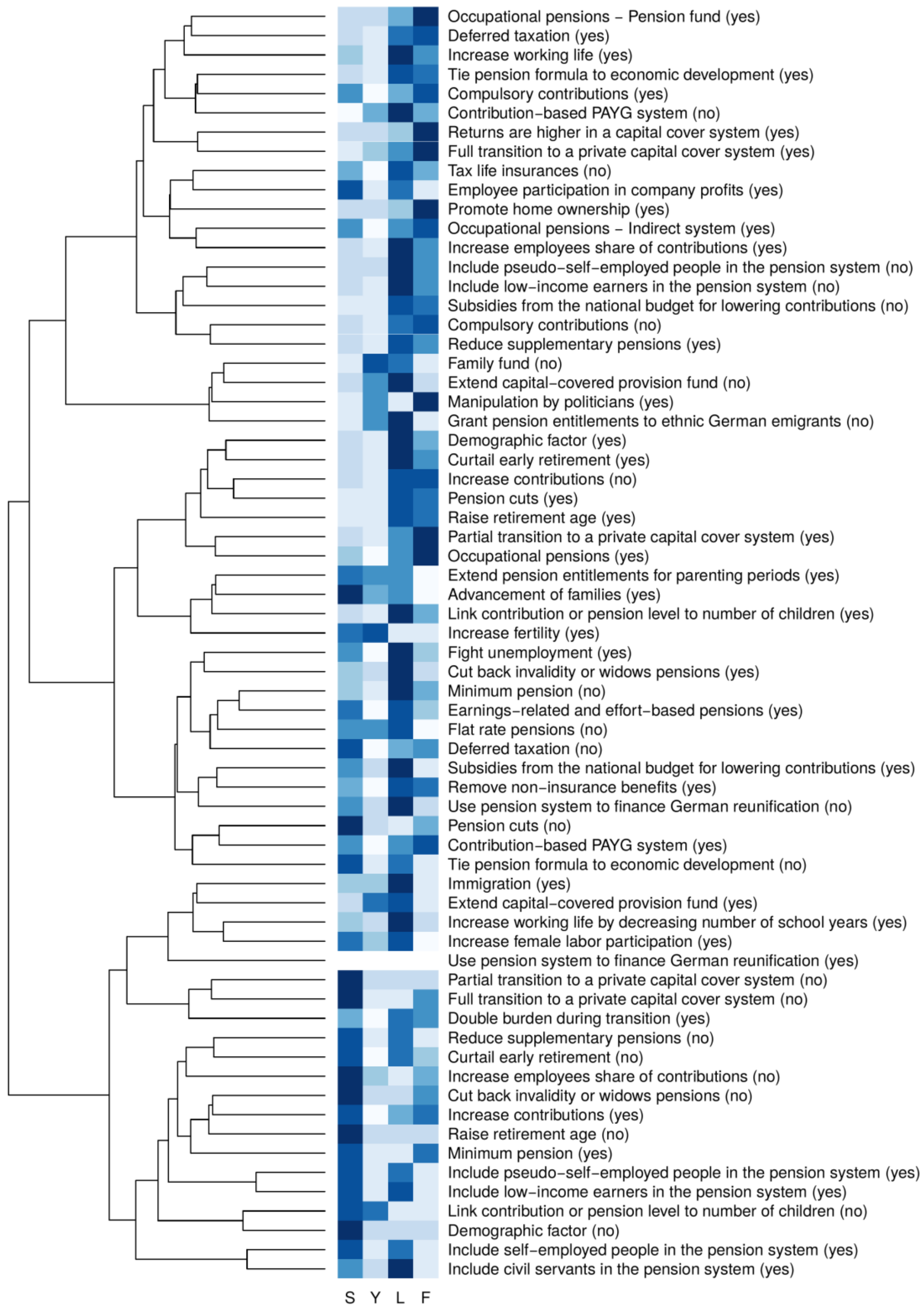


Figure 4 illustrates the consequences of applying a decreasing threshold value to the normalized actor congruence network. The four visualizations are based on the complete time period from 1993 to 2001. In the first panel, a relatively high threshold value of 0.6 retains only the most intense edges and therefore gives a clear picture of the so-called “islands” in the weighted network. In particular, the two competing coalitions are visible, and two smaller coalitions are displayed as well—one of them with financial actors and the other one with a subdiscourse related to employers’ associations. While these four core coalitions are visible, their location vis-à-vis each other remains unobservable. Only with a decreasing threshold, more details become gradually visible, among other details the relative location and connectedness between these groups. At the same time, however, zooming in also implies that the structure is less easy to interpret, especially with regard to subgroups. Therefore setting a threshold value is a tradeoff between too little information and too much complexity. In a sense, one has to filter out the “noise” and retain the “signal” by setting the threshold value in an explorative way. There is no rule of thumb because the distribution of edge weights depends on many factors that are specific to the case study, data source, time period etc. However, imposing a threshold value is only helpful for purposes of visualization; any formal community detection algorithm can be applied to the weighted network matrix.

Finally, Figure 5 shows a hierarchical cluster analysis of the Jaccard-normalized concept congruence network. Only concept–agreement tuples with at least 12 mentions are retained for this analysis. While the dendrogram on the left shows that there are approximately three clusters or “frames”, the different shades of blue in the level plot provide a micro-level foundation for the frames at the actor level: the darker the color, the more frequently the tuple was mentioned by social interest groups/trade unions (S), interest groups for young people (Y), liberal interest groups and trade unions (L), and financial market actors (F), respectively, with each line showing relative frequencies in a row-standardized distribution. Trade unions have a very coherent frame in the lower third of the plot, which centers around adjustments to the existing pension system, and financial actors and employers’ associations share a joint frame in the upper third of the diagram, revolving around privatization and private savings. The frame in the middle is politically moderate and features several sub-frames. One of them, for example, is concerned with fertility-related measures and is jointly advocated by young people’s interest groups and employers’ associations. Of course, alternative visualizations or analyses based on network layouts and/or other types of subgroup analysis would be possible with the same data.

Figure 5: Concept network. Hierarchical cluster analysis of the Jaccard-normalized concept congruence network (dendrogram on the left). Partitioning of concept–agreement tuples into actor categories for easier interpretation of the frame clusters at the actor level (level plot in the middle). Darker shades of blue indicate larger relative shares of activity by the actor group denoted at the bottom. S = Social interest group or trade union; Y = Young interest group; L = Liberal interest group or employers' association; F = Financial market actor. Source: Leifeld (2016).



7 Inferential network analysis for policy debates

There are two different types of research questions that can be answered using discourse network analysis. One of them relates the macro topology, or aggregate structure, of a discourse network to external variables like policy change or institutional variation between debates. For example, how can coalition dynamics explain a reform; how can the internal structure of competing coalitions explain their policy success or failure; how can the polarization of a debate be explained by events like elections or scientific reports; or in how far is it possible to relate policy change to shifting coalition memberships of decision-makers? These questions imply a research design at the macro level of a debate, which means that at least one of the variables of interest affects the whole network and that descriptive or explorative methods such as subgroup analysis or centrality are employed.

The other fundamental type of research question is concerned with micro-level mechanisms of political discourse. The explanandum is the topology of the network as generated by a sequence of statements. In other words, one would like to understand how discourse works by identifying what behavioral mechanisms and exogenous variables can jointly explain whether any actor a supports or rejects any concept c at any given point in time. Modeling the joint probability of all statements is equivalent to modeling the data-generating process governing political discourse.

Several candidate models for inferential network analysis exist, but most standard models are not ideally suited for inference on policy debates. The Exponential Random Graph Model (ERGM) treats time only implicitly and does not discriminate between positive and negative ties (Robins et al. 2007). The Temporal Exponential Random Graph Model (TERGM) (Hanneke, Fu and Xing 2010; Leifeld, Cranmer and Desmarais 2015) and the Stochastic Actor-Oriented Model (SAOM) (Snijders, van de Bunt and Steglich 2010) both assume discrete time periods for measurement purposes, but partitioning a discourse network into arbitrary time slices would likely alter the topology of the network and the statistics to be incorporated. Relational event models as proposed by Butts (2008) permit modeling time and the order of events more explicitly, but the original model and its model terms do not support signed edges (that is, agreement and disagreement in the case of discourse networks). Lerner et al. (2013) suggest an extension of the relational event model for signed networks, but the model terms are confined to one-mode networks. Brandenberger (2016) and Leifeld and Brandenberger (2016) extend relational event models to the case of bipartite signed graphs with time-stamped edges—that is, actors refer to concepts in a continuous-time setting, and these statements can have complex interactions that lead to coalition formation, the emergence of frames, issue attention cycles, and other properties of empirical debates. These complex interactions are parameterized by modeling the dependencies explicitly as covariates, including them in the regression equation, and estimating their relative importance in the data-generating process.

Relatedly, Leifeld (2014) reports the results of an agent-based simulation of political discourse. The model is not based on any micro-level data but rather proposes several theoretically plausible micro-level mechanisms and tests the implications of combining these effects for the topology (polarization, coalition formation etc.) of the resulting discourse network. The results indicate that a combination of several relatively simple micro-level dependency statistics like concept popularity, endogenous coalition formation, or the coherence of government actors already produces discourses that are reasonably in line with empirical case studies of discourse networks. Any of the mechanisms specified in the theoretical model can as well be formulated as a model term in a relational event model in order to estimate the relative importance of these effects based on real-world observations.

To give a rough non-technical intuition, relational event models for bipartite signed graphs (Leifeld and Brandenberger 2016; Brandenberger 2016; extending Butts 2008 and Lerner et al. 2013) work as follows. The explanandum is the observed sequence of statements. First, a left-censored survival model is used to estimate the probability that actor a refers to concept c at a specific time point or, equivalently, the waiting time until actor a refers to concept c. The probabilities for the different statements are conditionally independent given some exogenous covariates like actor type or concept type and functions of the statement sequence up to the respective time point. These functions capture endogenous dependencies between observations, for example recent concept popularity or indirect interactions between actors via concepts. The joint probability of the statement sequence is the product of all individual statement probabilities. A second aspect of the statement sequence is the type of a statement (positive or negative) given that the statement has been observed. This is estimated using a generalized linear model, more specifically a logistic regression model if the sentiment was coded as a binary variable. The odds of observing a positive rather than a negative statement are conditionally independent given some exogenous covariates and functions of the statement sequence up to the respective point, similar to the previous case. Again, the product of the individual probabilities for each statement type makes up the overall probability of observing the whole sequence of statement types. Both aggregated probabilities, the referral probability/waiting time and the statement type probability, can be multiplied to compute the overall probability of observing the sequence of statements, including frequency and type of statement. The first component of this probability is the *rate component* and the second one is the *type component*. Estimation of model parameters for both components can be done separately or jointly via maximum likelihood estimation.

In both cases, the specification of the endogenous dependencies is done by computing network statistics that take into account all previous statements. As previous statements are presumably less relevant the longer ago they took place, each statement's contribution to a statistic is weighted by a function of the time that has passed between the statement and the current time point. The user specifies the functional form of this temporal weighting scheme for the dependencies, e. g., by setting the so-called "half-life" of statements.

So far, this exposition closely follows Lerner et al. (2013). The task that is specific to discourse network analysis is tailoring the dependency functions to signed two-mode networks as in the following examples. *Actor activity* sums up how often the same actor has issued statements, weighted by time. For example, the more active an actor has been so far, the more likely the actor will make a statement at the upcoming time point. *Concept popularity* is a similar dependency statistic for the number of times a specific concept has been mentioned recently, which captures temporal clustering of concepts. *Inertia* measures the tendency of the actor—concept combination to have appeared before. *Balanced four-cycles* between actors capture the tendency of actors to follow the positive and/or negative concept usage patterns of other actors more multiple times. For example, if actor a_1 has supported concept c_1 and rejected c_2 in the past statement sequence, and a_2 has also supported c_1, this increases the probability that a_2 rejects c_2 as well at the current time point if actors 1 and 2 have a positively balanced relationship. To quantify this tendency, cases where the first three statements of this pattern occur, that is, where a balanced, open four-cycle exists, are counted and weighted temporally. The larger this quantity, the higher the expected probability that a statement is soon made that closes this balanced four-cycle. A similar model term can be designed for *negatively balanced four-cycles*, where the two actors mention statements in opposing ways more than once. Both model terms operationalize the idea of coalition formation by adopting each other's opinions.

Many more complex endogenous dependency statistics can be defined and added to an empirical model of the discourse at hand. Any count over the previous statements is allowed, possibly in combination with exogenous data. This flexibility allows the researcher to specify any kind of theoretical process that may be potentially responsible for the observed sequence of statements, that is, for the topology of the policy debate. Like in an ERGM context, this specification of dependency statistics must be sufficient in the sense that it covers all endogenous dependencies between statements; otherwise the remaining coefficients cannot be interpreted in a meaningful way. To ensure that this is the case, goodness-of-fit procedures for the endogenous properties of the temporal network are an important tool. These procedures simulate new sequences of statements from the model and compare structural properties of the observed and the simulated statement sequences. If both match up well, the dependencies have been modeled sufficiently. Development of techniques for goodness-of-fit assessment is an ongoing task.

There may be several goals of such an analysis. First, a micro-level explanation of how political discourse works can be informative for the case study at hand. The models suggested here are parametric in the sense that relative weights are estimated for each model term. This permits theory development and testing. Second, inferential network analysis may help to compare the underlying mechanisms across policy debates from different institutional settings. For example, how does newspaper-based political discourse differ from other kinds of arenas, or how does political discourse in one country differ from political discourse in another country? This can be assessed by comparing the coefficients for the different model terms. And third, inferential analysis can be employed to predict the future of a policy debate, at least over a short time period. A software implementation of relational event models for bipartite signed graphs is available in the *rem* package (Brandenberger 2016), which belongs to the *xergm* suite of *R* packages (Leifeld, Cranmer and Desmarais 2015). Currently, a major obstacle to inferential discourse network analysis is the availability of datasets. As many statements are required for such an analysis, semi-automatic statement recognition will be an important tool for generating large datasets.

9. Conclusion

Discourse network analysis is a versatile methodological approach, which combines qualitative, category-based content analysis with the full array of descriptive and inferential network analysis. It has been used to describe the structure of policy debates, derive interesting quantities of debates like the degree of polarization, the presence of coalitions, coalition-switching behavior of actors, brokerage, and cohesion or congruence of coalitions as well as the dynamics of policy debates over time. Such a descriptive mixed-methods approach to the analysis of empirical political discourse is useful for operationalizing important aspects of public policy frameworks like advocacy coalitions, discourse coalitions, policy brokers, issue attention cycles, political waves, or frames. Moreover, in contrast to prevalent empirical approaches to policy networks, it offers a temporally explicit process perspective rather than an analysis of cross sections of a policy network (e. g., using interview data). The approach comes with its own validity and reliability issues (Leifeld 2013; 2016), just like other approaches, but it paves the way for a new array of research questions related to endogenous processes in policy processes, especially with regard to policy beliefs and subsystem dynamics. A promising avenue for future research is the application of specialized inferential network analysis techniques for understanding the data-generating process that governs policy debates and ultimately for predicting political discourse.

Three pertinent problems plague discourse network analysis, and current and future research needs to tackle these issues: First, semi-automatic statement recognition is an active research frontier that has the potential to save a tremendous amount of manual coding efforts and at the same time potentially increase the reliability of the coding. The most promising directions may be a supervised multi-step prediction procedure based on named entity recognition, or syntactic parsing combined with a classification of identified nodes into meta-categories. Second, methods of inferential network analysis for bipartite signed graphs with time-stamped edges need to be implemented and improved in order to render inference on political debates a routine task (Brandenberger 2016; Leifeld and Brandenberger 2016). And third, abstractions from the actor–concept–sentiment coding scheme can offer interesting operationalizations of other policy theories or frameworks. For example, one could devise coding schemes for political claims analysis (Koopmans and Statham, 1999) or the Narrative Policy Framework (Jones and McBeth, 2010) by redefining statements to contain variables such as "addressee" or "hero" and by defining sensible criteria for deriving networks from these structured data. These new developments will greatly facilitate the comparison of empirical discourses across space, time, arena, institutional context, and theoretical framework.

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