

Political Discourse Networks - The missing link in the study of policy-oriented discourse*

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Empirical research on political discourses is usually either actor-centered or content-oriented. This paper introduces a novel methodology which closes this gap by combining social network analysis with qualitative content analysis. A special emphasis is put on the systematic analysis of longitudinal discourse dynamics. The static and dynamic methods are applied to German pension politics in order to elucidate how this perspective may help to understand a discourse. While the first part of the paper demonstrates how political discourses can be analysed empirically, the second part subsequently shows how discourse network analysis can be employed to theorise about political discourse. An agent-based computational model is presented where governmental actors and interest groups make statements about their preferred solution concepts for a given policy in a round-based game. Preferences in this model are endogenously shaped based on prior states of the discourse. The outcomes of the simulation model are analysed by using the approach presented in the first part of the paper.

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1 Introduction

A political discourse can be defined as “the formal exchange of reasoned views as to which of several alternative courses of action should be taken to solve a societal problem” (Johnson and Johnson, 2000). There has been a substantial body of research about political discourse (for an overview, see Janning et al., 2009). Despite this multitude of theoretical and empirical contributions, there is a gap between content-oriented and actor-centered approaches to political discourse. This paper will shed light on this missing link and introduce a novel methodology for analyzing political discourses empirically as well as theoretically. The approach is called discourse network analysis (DNA) and is a combination of qualitative content analysis and quantitative social network analysis.

The structure of the article is as follows: The second section briefly reviews existing approaches to political discourse and distinguishes content-oriented from actor-centered approaches. The new methodological framework for analyzing political discourses is described in section 3 and succinctly applied to German pension politics where examples are required. Section 4 tries to explain some of the general findings from the empirical part in a theoretical way by employing an agent-based computational model of discourse along the lines of the discourse network approach. The conclusion in section 5 will finally summarise the theoretical and empirical findings and discuss the advantages and drawbacks of discourse network analysis.

2 Literature review

The study of elite political discourse entails two rather different approaches. One of them is concerned with the contents of a discourse. Typical questions are: Which competing frames exist, how are they connected to political goals and power, and which concepts in the discourse are related to each other? This content-oriented approach is typical of critical discourse analysis (Wodak and Meyer, 2009), semantic network analysis (Brandes and Corman, 2003; Popping, 2003) and analyses of legitimacy discourses as conducted at the research center “Transformation of the State” (Nullmeier and Wrobel, 2005; Hurrelmann et al., 2005, 2007, 2009): In the latter example, arguments of legitimation and de-legitimation are identified based on a systematic analysis of newspaper articles to answer the question whether de-parliamentisation and transnationalisation erode the sources of legitimacy of national political systems. In these studies, legitimation patterns are occasionally linked to the actors who use them. However, the focus

is clearly on the revelation of patterns in the contents of the political discourse while actors play a subordinate role.

In contrast, the actor-centered approach to political discourse deals with configurations of policy subsystems along the lines of the actors' preferences or ideas. The actor-centered approach thus concentrates on changes in the mutual attachment of actors. These changes may ultimately explain policy change. Examples of actor-centered approaches to political discourse are the Advocacy Coalition Framework (Sabatier and Weible, 2007), Punctuated Equilibrium Theory (Baumgartner and Jones, 1991), epistemic communities (Haas, 1992) and policy paradigms (Hall, 1993). The Advocacy Coalition Framework provides a typical example: Actors are grouped into approximately two coalitions. Policy core beliefs are the "glue that binds coalitions together" (Sabatier and Weible, 2007), i. e. beliefs are more similar within a coalition than between coalitions. There are constant attempts of the coalitions to convince each other of their policy belief systems. This interaction constitutes the political discourse as defined at the outset of this paper. If external events lead to learning processes and changes in the affiliation of pivotal actors to coalitions, policy change becomes likely. The focus of this approach is on the learning behaviour of actors while the different concepts within the discourse play a subordinate role.

Both approaches, content-oriented and actor-centered, treat the connection between actors and concepts as a secondary interest. They do not analyze the co-evolution of actor configurations and ideas in a systematic way. As Steensland observes, "few existing studies link frames with the actors who sponsor them, thus presenting an oddly disembodied picture of framing processes" (Steensland, 2008, 1031). In addition, discourses, let alone the co-evolution of actors and ideas, are rarely systematically analyzed in a longitudinal way: "This dimension of policymaking has proven especially difficult to model. Like subatomic particles, ideas do not leave much of a trail when they shift. [...] We need more studies of the evolution of policy over time, a subject that has often been neglected relative to static, one-shot comparisons of policy across nations" (Hall, 1993, 290 ff.).

One of the few exceptions is political claims analysis (Koopmans and Statham, 1999), which tries to establish the missing link between actors and contents in a discourse by employing a distinct set of methods, particularly a classification of actors as well as frames on a one-dimensional pro/contra scale and time series graphs of discourse activity. However, Leifeld and Haunss (2010, forthcoming) show that the approach presented in this paper is complementary and may offer many insights previously hidden

to political claims analysis. Another approach that tries to bridge actor-centered and content-oriented perspectives are discourse coalitions (Hajer, 1995). Yet the approach of discourse coalitions aims at analyzing discourses in a qualitative manner, while the methods presented in this paper aim at measuring policy discourse in a more formalised way.

The approach presented in this paper, Discourse Network Analysis (DNA) (Leifeld, 2009a,b; Leifeld and Haunss, 2010; Janning et al., 2009), adopts an entirely relational perspective. It combines qualitative content analysis and quantitative social network analysis in order to conceptualise and measure the co-evolution of actors and concepts in a dynamic way. It is essentially a tool for the measurement or observation of a discourse and can be combined with many of the above-mentioned theoretical concepts underlying the analysis of political discourse, including discourse coalitions, political claims-making, legitimacy discourses, advocacy coalitions, and epistemic communities.

The approach is closely related to and can be integrated with the policy network approach (Adam and Kriesi, 2007). Policy network analysis is actually a methodological toolbox (Kenis and Schneider, 1991) and can be combined with many theories (Lang and Leifeld, 2009). In this broad definition of policy network analysis, discourse networks are merely one relational type beside other relations such as resource exchange between actors or common membership in committees. Discourse networks can be conceived of as an extension of policy network analysis to discursive structures. This, however, presupposes an actor-centered perspective. Discourse network analysis is in fact broader in scope because the relations between concepts in the discourse are also part of the relational model. The next section will outline the methodology of discourse network analysis and briefly apply it to German pension politics whenever examples or illustrations seem appropriate.

3 Discourse network analysis

3.1 Encoding statements

Discourse network analysis is a combination of social network analysis (Wasserman and Faust, 1994) and category-based, computer-assisted, qualitative content analysis. Like in content analysis, a coder assigns categories to text portions, but the unit of analysis is different. In discourse network analysis, only statements are coded. A statement is a part of the text where an actor expresses his/her beliefs or solution concepts for the

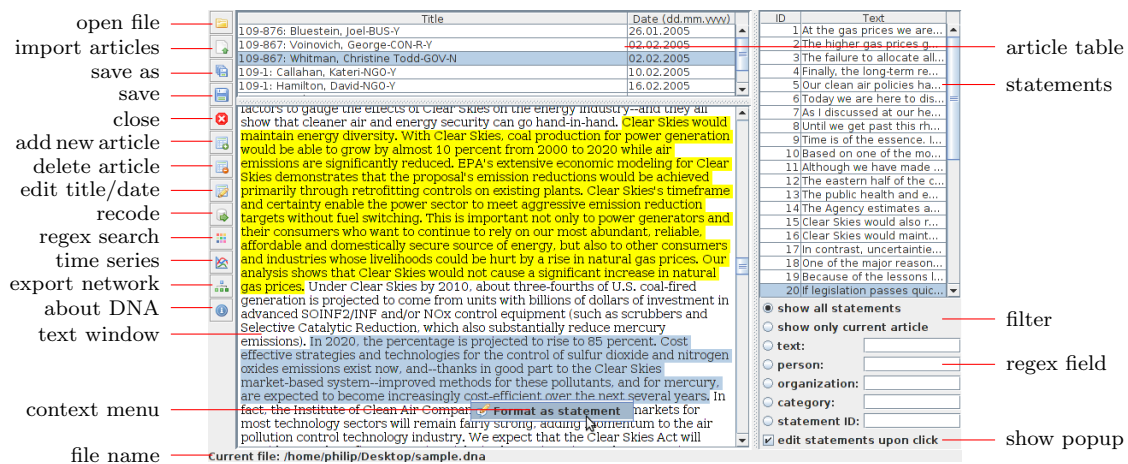


Figure 1: The main window

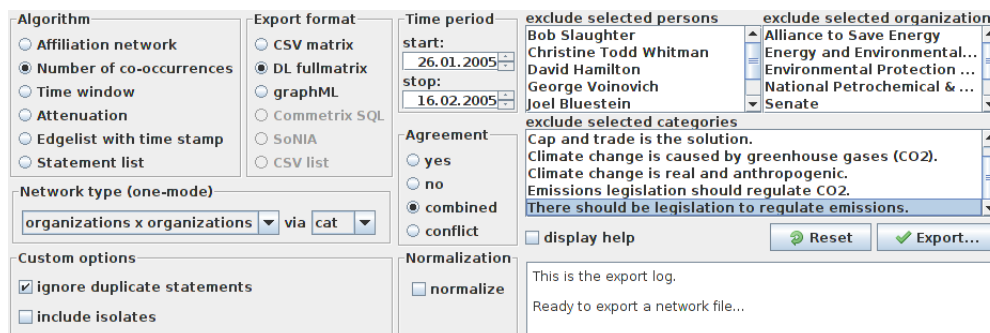


Figure 2: Network export window

problem.¹ Whenever a statement is encoded, the coder not only assigns a category or concept, but also the name of the individual and/or organisation that this concept can be attributed to, and a dichotomous variable indicating whether the actor agrees to the concept or not. Text material to be encoded may stem from newspaper articles (e.g. [Leifeld and Haunss, 2010](#)), position papers of actors, interview data, or parliamentary protocols (e.g. [Fisher, 2009](#)).

To facilitate the coding procedure, a free-to-use software called Discourse Network Analyzer (DNA) has been developed.² The software serves two purposes: Assigning

¹In the case of German pension politics, for example, such concepts could be “increase fertility to decrease the old-age dependency ratio”, “promote immigration of young foreigners to boost fertility”, “increase women’s share in the labour market to close the pension gap”, “decrease the level of pensions”, “increase the retirement age”, etc. In other contexts, these solution concepts have been referred to as “policy instruments”.

²The software Discourse Network Analyzer (DNA) and a comprehensive manual can be downloaded from <http://www.philipleifeld.de>. It is currently being employed in several research projects, among them the large-scale Comparing Climate Change Policy Networks (Compon) project, which compares political discourses on climate change in approximately 20 countries (<http://www.compon.org>).

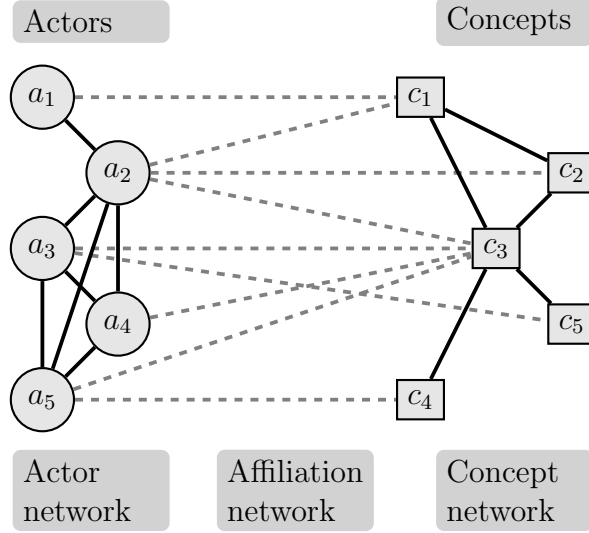


Figure 3: Simplified illustration of the discourse network model

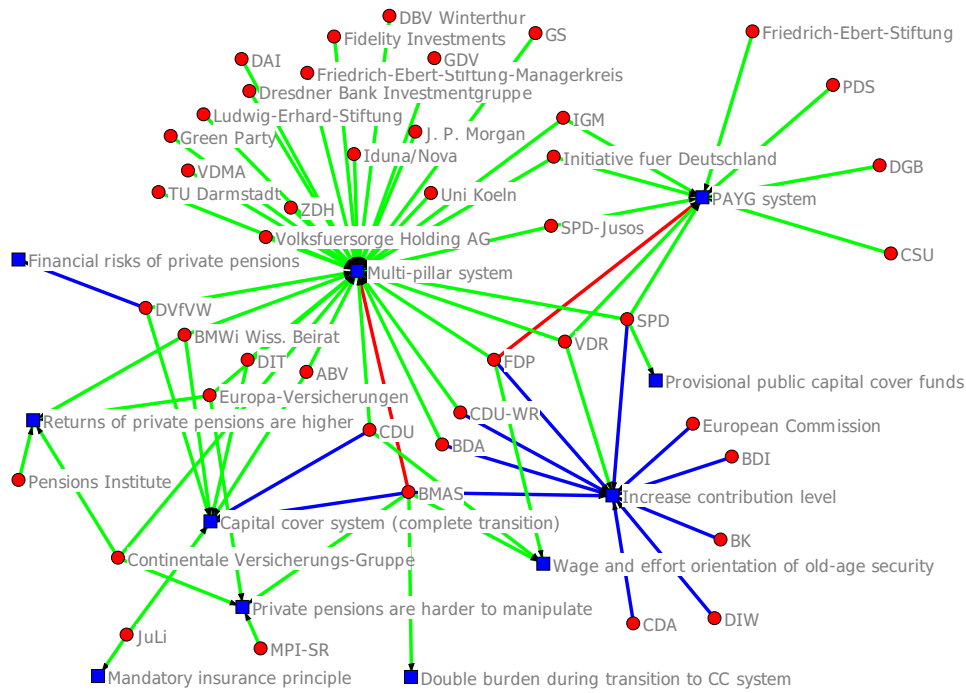
statement tags to text data, and then converting these structured data into networks. Figure 1 shows a screenshot of the main coding window. Once coding has been finished, networks can be exported to various file formats for use with network-analytic software packages like Ucinet, Netdraw, visone, Commetrix, SoNIA or statnet/R. Figure 2 shows a screenshot of the export window of DNA. To generate discourse networks from the structured data, several algorithms can be used. Their underlying principles will be described in the remainder of this section.

3.2 Affiliation networks

Figure 3 shows an illustration of the basic descriptive network model. There is a set of actors, $A = \{a_1, a_2 \dots a_m\}$, and a set of concepts, $C = \{c_1, c_2 \dots c_n\}$. An actor can either agree or disagree with a concept. Thus there are two relations between actors and concepts, one for agreement and one for disagreement: $R = \{r_1, r_2 \dots r_l\}$ with $l = 2$. There is also a set of discrete time points $T = \{t_1, t_2 \dots t_k\}$ because the discourse network can be repeatedly observed.

The most basic form is a bipartite graph of actors referring to concepts either in a positive or in a negative way at a certain time point. The bipartite graph is called *affiliation network*. It is captured by this equation:

$$G_{r,t}^{\text{aff}} = (A, C, E_{r,t}^{\text{aff}}) \text{ with } \{a, a'\} \notin E_{r,t}^{\text{aff}} \wedge \{c, c'\} \notin E_{r,t}^{\text{aff}} \quad (1)$$



Note: Green edges indicate agreement, blue edges disagreement and red edges both.

Figure 4: Affiliation network; system change in German pension politics 1998–1

This corresponds to the dashed lines between actors and concepts in the illustration. Applied to empirical data, an actor is connected to a concept if (s)he makes a statement in the media. The affiliation network can simultaneously show actors and concepts as well as their interrelations, which already goes well beyond most existing measurement approaches to political discourse. Moreover, the data can be subdivided into several time slices in order to obtain repeated measurements of the discourse. Please note that there are two separate affiliation networks, one for the agreement and one for the disagreement relation. They can be easily combined in a multiplex network.

Figure 4 shows an example of an affiliation network. The bipartite graph is based on newspaper articles from the German newspaper Frankfurter Allgemeine Zeitung (FAZ) in the first half of 1998.³ All articles where an organisational actor makes a statement about the paradigm shift from a pay-as-you-go pension system to a capital cover pension system are covered by the analysis. The figure shows a multiplex graph; green edges

³Please note that newspapers may systematically bias the appearance of actors or opinions. However, the alternatives are scarce: Parliamentary protocols restrict the number of reported actors to few invited interest groups who already belong to the in-group of politics anyway. This would undermine the very idea of the mechanisms of political discourse. Interviewees are nowadays hard to acquire, and they suffer from other kinds of bias. In empirical studies, a cross-validation between several newspapers might be a viable solution.

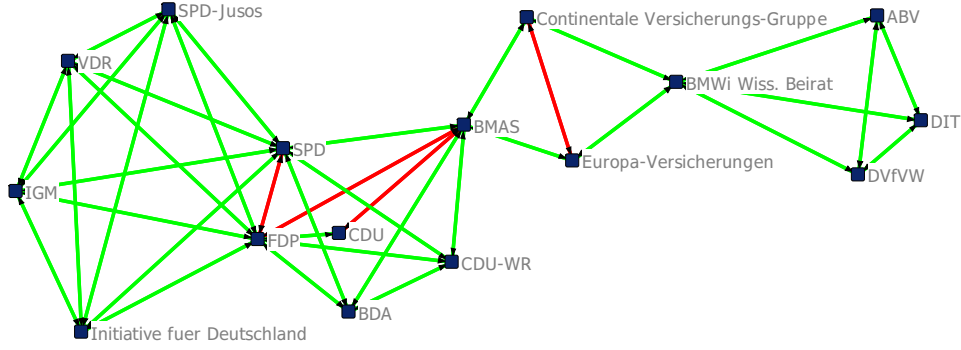
indicate that an actor agrees to a concept, blue indicates disagreement, and the red edges indicate cases where an actor shows both agreement and disagreement.

As for the interpretation, the affiliation network shows that a number of socially oriented actors like the trade unions and leftist parties are status-quo oriented and favour a pay-as-you-go pension system while most employers' and industry associations express objections to increasing the pay-as-you-go contributions. Only VDR, the association of public pension agencies, takes a strong position by agreeing to both issues because their existence is at stake and increasing the contribution level would offer more leverage for keeping the PAYG system. The liberal party FDP sends mixed signals before the upcoming election in September 1998. A set of liberal actors together with representatives of banks and insurance companies, who have incentives to sell private old-age insurances, advocate a complete transition to a private capital-cover system or at least a partial introduction as featured in a multi-pillar system. In contrast, the ruling parties and ministries reject a complete transition and rather opt for a mixed system.

3.3 Congruence networks

This one-shot description is not very interesting in itself. It becomes more interesting if several time slices are measured, and if changes in the affiliation of critical actors to certain solution concepts can be observed. However, it is quite difficult to establish whether two actors actually exhibit high or low degrees of belief overlap, given this highly complex graphical representation of the discourse. One might not only be interested in how actors relate to concepts, but also in how far discourse coalitions emerge from this structure. The basic idea is that the more different solution concepts two actors agree (or both disagree) on, the more similar are they in terms of preferences in the discourse, and the more likely are they to belong to the same discourse coalition or advocacy coalition. Thus, it is straightforward to move from a bipartite affiliation graph to an adjacency graph where actors are connected to other actors and where the edge weight between these actors represents the number of common concepts. The overall topology of the resulting *congruence network* can be used as a map of the discourse where clusters of actors represent advocacy coalitions. The congruence network provides an intuitive way of conceptualising and measuring advocacy coalitions (or other actor-centered discourse constructs, depending on the type of concepts used for categorisation).

If the bipartite graph is a representation of a rectangular matrix $\mathbf{X}_{m \times n}$ where actors occupy the row labels and concepts the column labels and where only the agreement relation or only the disagreement relation is shown, the congruence network can be



Note: Only $w(u, u') \geq 2$ are displayed. Green edges indicate $w = 2$, red edges $w = 3$.

Figure 5: Congruence network; system change in German pension politics 1998–1

obtained by computing $\mathbf{X}\mathbf{X}^T$, which yields a square actor \times actor matrix with the number of shared concepts as the cell entries. Both relations can then simply be added in order to combine positive and negative citations of concepts. In graph-theoretical notation, the congruence network is captured by the following equation:

$$G_t^a = (A, w_t) \text{ with } w_t(a, a') = \sum_{r=1}^l |E_{r,t}^{\text{aff}}(a, C) \cap E_{r,t}^{\text{aff}}(a', C)| \quad (2)$$

According to the Advocacy Coalition Framework and other theories, two or more coalitions should be expected in typical policy domains where issues are contentious (e. g. environmentalists versus industry interests in climate change politics, small- and medium enterprises versus large companies in the conflict on software patents, social and elderly interest groups along with trade unions versus liberal and employers' interest groups and insurance companies in pension politics, etc.). Depending on the scope, it may make sense to code conflicts over several issues or to go down one level and also include arguments for specific concepts or for policy instruments in the coding procedure. This is likely to make the observed discourse more complex. In the latter case, the congruence network can serve to identify the underlying cleavage lines that are actually present in the discourse, and assess how they change over time. In the pension politics example, there could theoretically also be differences between family-policy- and fertility-oriented interests and labor-market frames, or between the interests of employers and insurance companies, etc. The literature on German pension politics also suggests that the structure of coalitions changes over the course of the 1990s because new ideas are introduced, finally culminating the Riester reform in 2001, which is widely

acknowledged as a major policy innovation. Congruence networks are well equipped to measure and visualise these changes over time.

Figure 5 shows an example of a congruence network from German pension politics for the first half of 1998. The same data as depicted in figure 4 have now been converted to a congruence network of actors. To make the structure more easily visible, only edge weights where two actors agree at least twice are retained. Green edges represent two common positions, and red edges represent three common positions. As in figure 4, the spatial coordinates of the vertices are obtained by optimising a graph layout that tries to make the structure of the graph as easily interpretable as possible. In other words, only the presence or absence of ties should be interpreted, not the position of the actors. In this example, we can see that the responsible federal ministry (BMAS) takes a bridging role between insurance companies and some liberal organisations on the right, and all other political actors on the left. A longitudinal analysis may shed light on how the role of the BMAS changes over time and how stable the discourse coalitions actually are.

The point of congruence networks is to measure the mutual attachment of actors via their statements in the discourse. When analysing a political discourse in a conventional, qualitative way, the researcher usually implicitly tries to interpret which actors align with which other actors. This task is rather demanding for the human brain, so evidence can usually only be provided on an anecdotal basis instead of taking into account all relevant actors and concepts and their alignment. The researcher not only has to take into account who refers to what, but also has to calculate in a second step what other actors mention the same concept in the same way. Discourse network analysis may help to accomplish this task by systematising it.

3.4 Concept networks

The previous section has elaborated how an actor-centered perspective emerges from the affiliation network described in section 3.2. This reflects the actor-centered approach to political discourse as discussed in the introduction. The other direction to depart from affiliation networks is towards a content-centered approach to studying political discourse. Relevant questions are: What solution concepts go together in the discourse – thereby shaping coherent and transitive approaches to solving the policy problem –, and what concepts are separate? Under what circumstances do solution concepts become central or peripheral in the discourse? What aspects of the policy problem are linked by actors?

Mathematically, this is analogous to converting the affiliation network into an actor-based congruence network. But instead of measuring the similarity between actors, one computes the similarity between concepts in terms of common citations by actors:

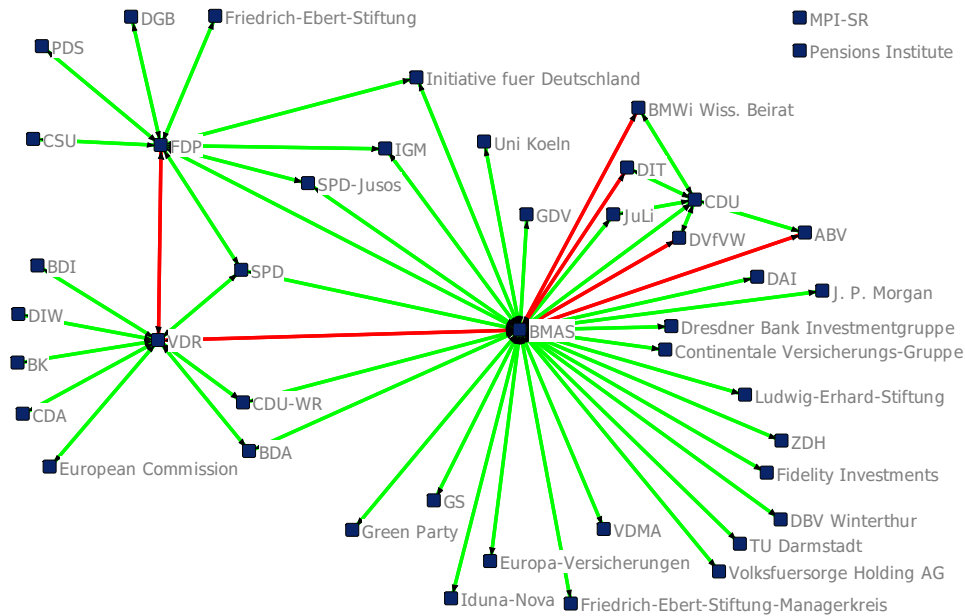
$$G_t^c = (C, w_t) \text{ with } w_t(c, c') = \sum_{r=1}^l |E_{r,t}^{\text{aff}}(c) \cap E_{r,t}^{\text{aff}}(c')| \quad (3)$$

This corresponds to the solid black lines between the concepts in the illustration shown in figure 3. Here, two concepts are connected if an actors agrees or disagrees on both concepts. The edge weight is proportional to the number of actors citing the two concepts in the same way. For example, if five actors agree to increasing the pension entrance age, and the same five actors mention (independently from each other) that they would like to cut down the number of secondary school years in order to make people work and pay into the PAYG system earlier, and if three actors say they reject increasing the pension entrance age and also reject cutting down school years, the two solution concepts to the pension problem are linked with an edge weight of 8. Aggregating these weights over all dyads of actors yields a map of the discourse like in the actor congruence network, but this time with concepts. Clusters in this topology of arguments can be interpreted as coherent approaches to solving the policy problem. The concept network can be used to find out which concepts are *empirically*, though not necessarily theoretically, linked to each other. For instance, fertility-related concepts and managerial concepts are surprisingly often linked to each other in the pension discourse. The reason may be that employers tend to interpret the pension problem as being caused by demographic change, which they believe to affect the composition of the workforce.

Concept networks can also be used as an indicator of topical overlap between advocacy coalitions. If actors speak past each other and coalitions call for different solutions without really referring to each other, there should be several largely disconnected clusters of concepts. Where actors frequently attack each other, the network of concepts should be denser and exhibit more overall clustering.

3.5 Conflict networks

So far, co-occurrence networks of actors or concepts have been representations of similarity between actors or between concepts. However, there is another information hidden in the original data: conflictual relations, or dissimilarity between vertices. For example, one actor would like to cut pensions while another actor rejects this measure. If a



Note: Green edges indicate $w = 1$, red edges $w = 2$.

Figure 6: Conflict network; system change in German pension politics 1998–1

discourse is viewed as a number of interactions between agents, then these two actors can be said to have a conflictual relation because one of them rejects the measure of the other actor.

Figure 6 provides an example which is based on the same data as all previous examples. Strong conflicts are red. Interestingly, while figure 5 suggested that insurance companies and liberal actors are somehow separated from the mainstream political actors in the congruence network, figure 6 proposes that there is not really a conflict between the two camps, even though they have distinct convictions. The federal ministry BMAS is an exception, but it also acts as a bridge between the camps in the congruence network. Conflicts mainly occur between parties and other mainstream political actors.

Another useful example of conflict networks is given by Leifeld and Haunss (2010), who create a multiplex network of the EU software patents case. In this application, both congruence and conflict are visualised as different colors. It is easy to see that congruence is prevalent mainly within coalitions, while conflict is almost only present between the coalitions, but not within them. This can be interpreted as a fight over political claims. In other words, topical overlap is large, and actors try to reclaim arguments. This is apparently much less the case in the pension politics application.

3.6 Dynamic discourse networks

As set out earlier on, one of the goals of discourse network analysis is the *dynamic*, or longitudinal, analysis of political discourse. Discursive interactions are conditional on past interactions. In statistical terms, discourse is non-stationary. One way to measure change over time is to subdivide the whole discourse into several time slices which are then compared either qualitatively or via measures of network correlation. For instance, a discourse can be compared before a reform and after a reform. Moreover, a discourse can be subdivided into monthly or annual time steps, and dynamic visualisation tools like SoNIA (Moody et al., 2005) can be employed to examine the changing roles of actors by generating a movie of the discourse network.⁴ This is basically a “discretisation” of time, which is actually continuous.

However, by using discrete time steps, one may lose important information. For example, in networks aggregated on an annual basis, a link is not established between two actors if one actor makes a statement in December and the other one in January. This is somewhat imprecise. Additionally, a special feature of political discourse is that meaning and context can change between time periods. If a concept is cited in one year, it may not necessarily have the same meaning in another year. For example, the interpretation of “basic pensions” changed gradually over the course of the 1990s from decreasing the pension level to introducing minimum pensions as a device against old-age poverty, with changes being so gradual that many cases cannot reliably be classified into either subcategory.

These problems can (at least for the most part) be solved by introducing a time window of a certain size \bar{w} . Figure 7 illustrates the time window approach. It is possible to watch a discourse network as a continuous-time movie where at every time point t links are only established between two actors if the relevant statements of the two actors were expressed not more than \bar{w} days ago. The network shown at time t in the animation is then a representation of the discourse between $t - \bar{w}$ and t . The problem outlined above is solved by moving the time window through the discourse at very small steps, e. g. on a daily basis. This is governed by the constant parameter s . Both, \bar{w} and s can be arbitrarily chosen. The result is a very detailed, dynamic, continuous-time visualisation of actor coalitions over time. It is easy to observe at what point in time critical actors leave one coalition and join the opponent, or when a cluster is absorbed by another cluster.

⁴All dynamic network algorithms presented here, as well as compatibility with relevant third-party software, have been implemented in the software Discourse Network Analyzer (DNA).

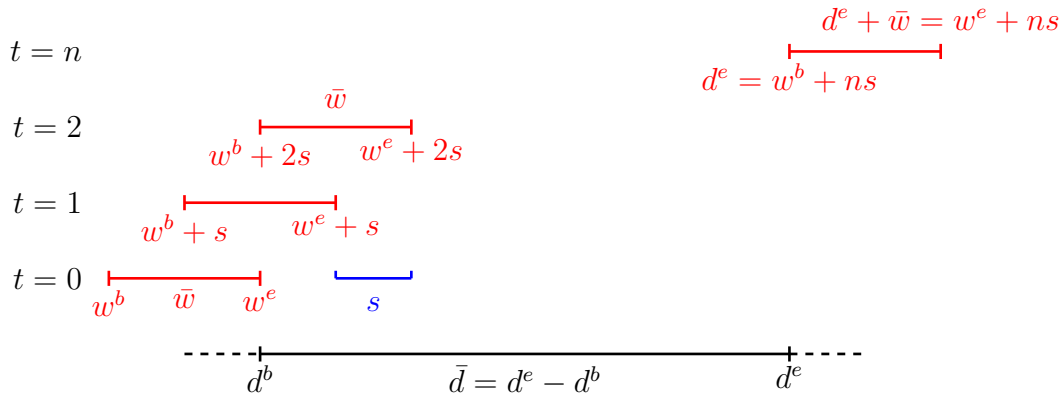
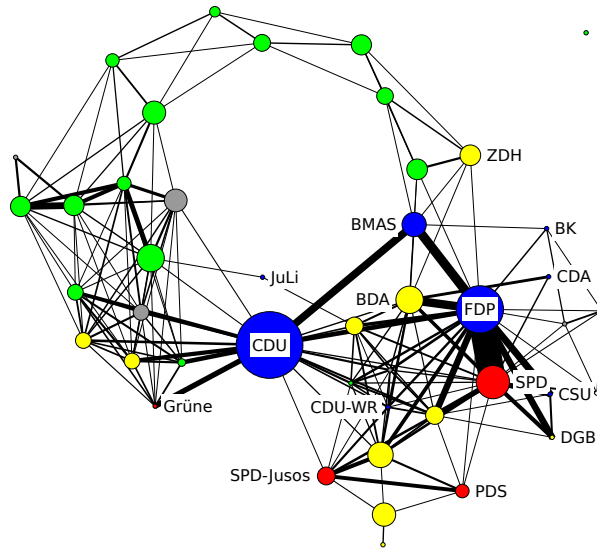


Figure 7: Illustration of the time window algorithm

Admittedly, movies are not the best form of representation when it comes to publishing research in journals or books. Nonetheless, it is quite easy to adapt the time window algorithm to make it compatible with static visualisations. Assume the weighted actor congruence network at time t_1 is saved in a square matrix \mathbf{X}_1 , the network at time t_2 in another matrix \mathbf{X}_2 , and so on. Then adding this stack of matrices yields a new matrix $\mathbf{X}_{1 < t}$ with rather high edge values. Multiplying this network with a constant, $n = \frac{\bar{d} + \bar{w}}{s}$, where \bar{d} is the total duration of the discourse in days, yields a normalised static network. In this resulting network, clusters are much more nuanced than in the simple congruence network. This static time window network is basically a representation of interactions between actors in the discourse, given the assumption that actors who make similar statements within a certain number of days respond to each other. It is a representation of the *average* time window slice that was obtained from the dynamic algorithm.

Figure 8 shows a visualisation of the data used above with $\bar{w} = 20$ and $s = 1$. It becomes obvious that the Christian-Democratic party CDU is the most central actor in the discourse if interactions are taken into account. There was a time period where a series of statements by insurance companies occurred, and the early 1998 government (the blue nodes) both started and ended this debate. Another interesting finding is the frequent positive interaction between FDP (the liberal party) and SPD (the social democrats). Apparently there was a substantial degree of positive coordination between the two parties (as reflected by the line width), possibly in prospect of a potential coalition government between the two parties after the upcoming election.

Instead of using a time window, it is possible to model the time between the statements of two actors directly as being inversely proportional to their probability of interacting. For example, if two matching statements occur within two days, one actor is likely to



Note: **Governmental actors** are blue; **opposition** is red; **interest groups** are yellow; scientific research institutes are gray; **banks and insurance companies** are green. Vertex size reflects betweenness centrality.

Figure 8: Time window algorithm; system change in German pension politics 1998–1

respond to the other actor. On the other hand, if the second statement is made after half a year, this is unlikely to be a reply. This idea can be employed to model interactions between actors in a more exact way than the time window approach. However, discussing the details of this so-called *attenuation algorithm* and its epistemological implications are beyond the scope of this paper.

4 Simulating political discourse

In section 3, discourse network analysis was presented as a tool to analyse empirical networks. This is an incomplete definition of discourse network analysis because the approach can be equally well applied to theoretical models. Discourse network analysis is rather a tool to measure and visualise a discourse, whether of empirical or theoretical origin. This section will prove this point by theorising about the evolution of political discourses over time. For this purpose, I outline several possible strategies that actors can employ in their endeavour to choose the solution concepts they would like to introduce as statements to the political discourse. After each round of concept-picking, the current state of the discourse is visualised as a congruence network.

Despite their effort, researchers rarely make the mechanisms explicit that underlie the dynamics of discourse. Empirical evidence suggests that the usage of solution con-

cepts to political problems is highly complex because actors choose their next statement contingent on what statements the other actors have previously come up with (c. f. section 3.6) and at the same time in compliance with their own ideology (as the bipolarised structures of empirical discourses suggest, c. f. Leifeld and Haunss 2010), to name just two out of several strategies. The aim of the simulation described here is to model heuristics of actors in a bottom-up approach and then evaluate how different strategies affect the development of a discourse.

4.1 Setup of the model

The simulation model assumes that there are two different types of political actors: governmental actors and interest groups. Each actor a adheres to one out of two adversarial ideologies. In the initial setup of the model, the number of actors belonging to each of the four possible combinations can be chosen by the researcher.⁵ As outlined in section 3.2, a discourse does not only consist of actors, but also of a set of concepts C . Again, the user can specify the number of concepts present in the discourse. Every concept is affiliated with one of the two ideologies, following a uniform probability distribution with $p = 0.5$ for each ideology. In the pension politics example, this could be a social versus a liberal ideology. Actors come with a history of five previously named concepts, which is also randomly generated during setup (under the restriction that the ideology of the initial concepts must match the actor’s ideology). Actors can update their statement history by choosing a new concept, naming it in the discourse, adding it to their history and then deleting the first concept from the history to make sure there are always the last five concepts saved in their history list.

Every actor follows one out of two objective functions, depending on whether the actor is an interest group or a governmental actor. The components of the functions are identical, but the weights can be different. The simulation is round-based. In every round, either an interest group or a governmental actor is randomly selected and makes a statement by maximising his or her objective function. The probability that a governmental actor is selected is governed by a constant $p(\text{gov})$, while the probability of an interest group is $1 - p(\text{gov})$. Making a statement entails evaluating all concepts by employing the objective function. This resembles a genetic algorithm, where a chromosome is ranked against other chromosomes and the fittest chromosome is selected for recombination. The current actor compares the fitness of each concept with the fitness

⁵The work on this agent-based model is in progress. The version presented here has been implemented in Java using the library RepastJ, but the model has not been published yet.

scores of all other concepts according to his/her fitness function and determines which concept is selected for the next round:

$$f(c) > f(c') \Rightarrow c \succ c' \quad (4)$$

This is a simplified model of the discursive activity of actors as previously measured using empirical data. They react to statements made by other actors by also citing certain concepts in the discourse. As in the dynamic models of section 3.6, discourse is non-stationary, and the discourse at time t is conditional on discourse at time $t - 1$.

4.2 Objective functions

Interest groups choose the concept that maximises the function set out in equation 5. If several concepts produce the same score – which rarely happens –, one of these concepts is randomly selected.

$$f^{ig}(c_i) = \beta_1 \text{IM}(c_i) + \beta_2 \text{AH}(c_i) + \beta_3 \text{CS}(c_i) + \beta_4 \text{AS}(c_i) + \beta_5 \text{CP}(c_i) + \beta_6 \text{RI}(c_i) + \beta_7 \text{GC}(c_i) \quad (5)$$

Likewise, governmental actors choose the concept that maximises the function presented in equation 6. The two functions are identical except for the different weights which can be arbitrarily set by the researcher. The seven components of the functions are described below.

$$f^{gov}(c_i) = \gamma_1 \text{IM}(c_i) + \gamma_2 \text{AH}(c_i) + \gamma_3 \text{CS}(c_i) + \gamma_4 \text{AS}(c_i) + \gamma_5 \text{CP}(c_i) + \gamma_6 \text{RI}(c_i) + \gamma_7 \text{GC}(c_i) \quad (6)$$

Each part of these functions assigns a value to the concept to be evaluated. In other words, at every time step, the actor who currently has a turn looks at each concept separately and decides how attractive it is to name this concept as a statement in the discourse. (S)he selects the most attractive concept for his/her statement. The reasoning that occurs in the mind of the actor is captured by equation 5 or 6. The researcher can decide which part of this reasoning is enabled and which one is disabled, or more exactly, the researcher can presuppose and combine different behavioral dispositions that make the actors choose one concept over another. By doing this, it becomes possible to observe how the structure of a political discourse develops across time given the assumption that actors are, for example, purely ideology-driven, or purely self-consistency-maximising, or a combination thereof, etc. The different heuristics the researcher can actually presuppose will be briefly sketched in section 4.3. Please note that it is possible to completely

switch off certain heuristics by setting the β or γ weights to zero. This is important because it allows to compare the effects of single heuristics.

To make the scores comparable across the parts, the values are usually normalised after each calculation. This normalisation is done via a normalising algorithm. It guarantees that the outcomes of all components of the objective function are scaled in the same way and that the same β or γ weights lead to comparable scores.

4.3 Elements of the objective function

Ideological match of actors (AM)

The first component of the function is a method that evaluates whether a concept matches the actor's own ideology. If this is the case, the concept gets a high score unless there are several matching concepts. The more concepts with a matching ideology are present, the lower is the score of each of these concepts. If the ideology of the concept does not match, the minimum score is assigned.

This method represents the classic view that interest groups have a rather fixed set of preferences and try to pull the outcome of policy-making into their ideological directions. It is compatible with (although it does not directly follow from) pluralist (Truman, 1951) and corporatist (Schmitter and Lehbruch, 1979) theory as well as the Advocacy Coalition Framework (Sabatier and Weible, 2007), which posit that advocacy groups engage in a fight over belief systems. In any case, it is straightforward to assume that interest groups will rather express statements that support their ideology than statements running against their own ideology. Ideology in this sense is not policy-oriented but more intrinsic. It can be conceived of as a latent variable pulling an actor into one out of two possible directions.

Actor's history (AH)

The second component of the objective function stems from social psychology. Individuals and also organisations as corporate actors try to maximise consistency with their previous statements. This results in an actor's own latest statement scoring highest, the one before second-highest, etc. Concepts which are not in the actor's history receive the minimum score.

This method is based on cognitive dissonance theory and its descendants (Abelson et al., 1968; Festinger, 1957): Aronson's self-consistency theory implies that actors strive for consistent views of themselves in order to avoid dissonance (Aronson, 1968). Cial-

dini, Trost and Newsom define consistency as the “tendency to base one’s responses to incoming stimuli on the implications of existing (prior entry) variables, such as previous expectancies, commitments and choices” (Cialdini et al., 1995). Actors obviously weight their own previous statements higher than other concepts because they want to maintain and communicate a coherent image of themselves, leading to path dependence of an actor’s statement choice.

Concept similarity (CS)

The concept similarity score of a concept is calculated as follows. A co-occurrence matrix is created which contains the similarities between all concepts. Two concepts are more similar, the more often an actor refers to both of them in his/her history. For every concept in the discourse, the method then adds up the similarities between this concept and each item in the history list of the current actor. This results in the total similarity between a concept and the current actor, based both on his/her history and the evaluations of all other actors. This of course presupposes perfect and complete information.

One rationale for this method is again the tendency of subjects to deny information that does not conform to their own beliefs (Aronson, 1968). At the same time, political actors strive for new arguments and concepts in support of their claims. As Hall puts it, “the struggle both for advantage within the prevailing terms of discourse and for leverage with which to alter the terms of political discourse is a perennial feature of politics” (Hall, 1993). Actors try to position themselves in the discourse, avoid being isolated with their claims, and they closely observe which other concepts are both popular and close to their own position. If they adopt such a claim, it is more likely that other actors will refer to them and in turn adopt their other concepts.

Actor similarity (AS)

The actor similarity score follows from the prediction of the Advocacy Coalition Framework (Sabatier and Weible, 2007) and other interest group theories (e.g. Baumgartner and Jones, 1991) that interest groups are organised in coalitions. According to the former theory, actors learn more easily from other actors if they are in the same coalition. A coalition, however, is not a stable and closed arrangement. It is rather constituted by the similarity of belief systems between actors. Consequently, actors identify other actors who are in the same coalition by measuring their overall belief similarity and then adopt one of their beliefs.

This is precisely what is done in the function: An actor first considers the histories of all other actors (i. e. their last five concepts) and computes their similarities to his/her own history list by counting the co-occurrences of concepts. The latest concept of the most similar actor is then assigned the highest score, the latest concept of the second most similar actor the second highest score, etc. If a concept qualifies for two distinct actors, the mean of their similarity scores is used. This method directly implements the idea of adaptation from actors who have similar belief systems.

Concept popularity (CP)

Statements in a political discourse are never randomly distributed over time. There is constant interaction between agents. They often pick up claims raised by other actors just because they are popular and because they can only be at the center stage of political discourse if they pick up all relevant aspects of a problem. A politician or a party that just ignores claims brought up by others will not be re-elected, and similarly a ministry will be criticised if it ignores important facts of the problem it is in charge of. This is particularly a feature of governmental actors, not so much of interest groups.

The concept popularity procedure therefore takes into account the current distribution of concepts over all actors. The concept that is mentioned most often receives the highest score; the second most frequent concept receives the second highest score, etc.

Rare concepts with an ideological match (RI)

Particularly interest groups find it worthwhile to revive a sleeping discourse in favor of their ideology. If there is a concept that has not been actively discussed for quite some time, it proves to be a good opportunity to pick up this concept and re-introduce it into the discourse in order to pull the debate into a certain direction. In public policy analysis, this strategy is situated somewhere between problem definition and agenda-setting in the policy cycle (for an overview, c. f. [Rochefort and Cobb, 1993](#)).

The rarity method works as follows: A concept is given a high score if it is not present in the history of any actor in the discourse and if the concept provides an ideological match. It receives a low score if it is present in the discourse and/or the ideology does not match. The more matching concepts are absent, the lower is the score of each of them.

Government coherence (GC)

The government coherence method serves two different purposes for interest groups and governmental actors. For every concept, it counts by how many other governmental actors it was previously chosen, i. e. in how many other governmental actors' history lists it is present. The more, the better.

For governmental actors, this is an important procedure because they usually share common goals – despite possible ideological differences due to coalition governments. In the German case, this is called “Richtlinienkompetenz”, but in other political systems, the various ministries are usually also tied together by common objectives, parties, coalition contracts or presidents. The aim of the method is to unify governmental actors by aligning them to each other and giving them a common line.

For interest groups, this method defines the degree to which they adhere to the line of the government. In consensual or corporatist political systems, β_7 should be high, while it should be low in majoritarian or pressure-pluralist systems (Lijphart, 1999).

4.4 Assumptions and limitations

There are some strong assumptions which may be abandoned in future versions of the simulation: Other actors like scientists, opposition, voters or the media do not play a role; the number of actors stays constant over the whole discourse; a discourse does not interfere with other topical discourses; the number of concepts is constant; there is only one agreement relation (unlike in the empirical model); new concepts are never introduced to the discourse; external perturbations (Sabatier and Weible, 2007) do not exist; exactly one statement is made at every new time step; actors observe all other actors' statements, i. e. there is complete and perfect information. For the sake of manageability, these factors are excluded in this first version of the model. It should be clearly noted that the model at this preliminary stage does not provide a complete picture of political discourse in reality yet. The main point of this exercise is to show how theory-building may work in the discourse network framework.

Another potential objection may be that all of the factors presented here do not involve a problem-solving dimension. Perhaps political actors are first and foremost interested in solving policy problems in an objective, enlightened, altruistic way and do not care so much about party politics, ideologies, etc. However, if this were true, the stable affiliation of actors to two distinct camps as found in most empirical studies ought not exist.

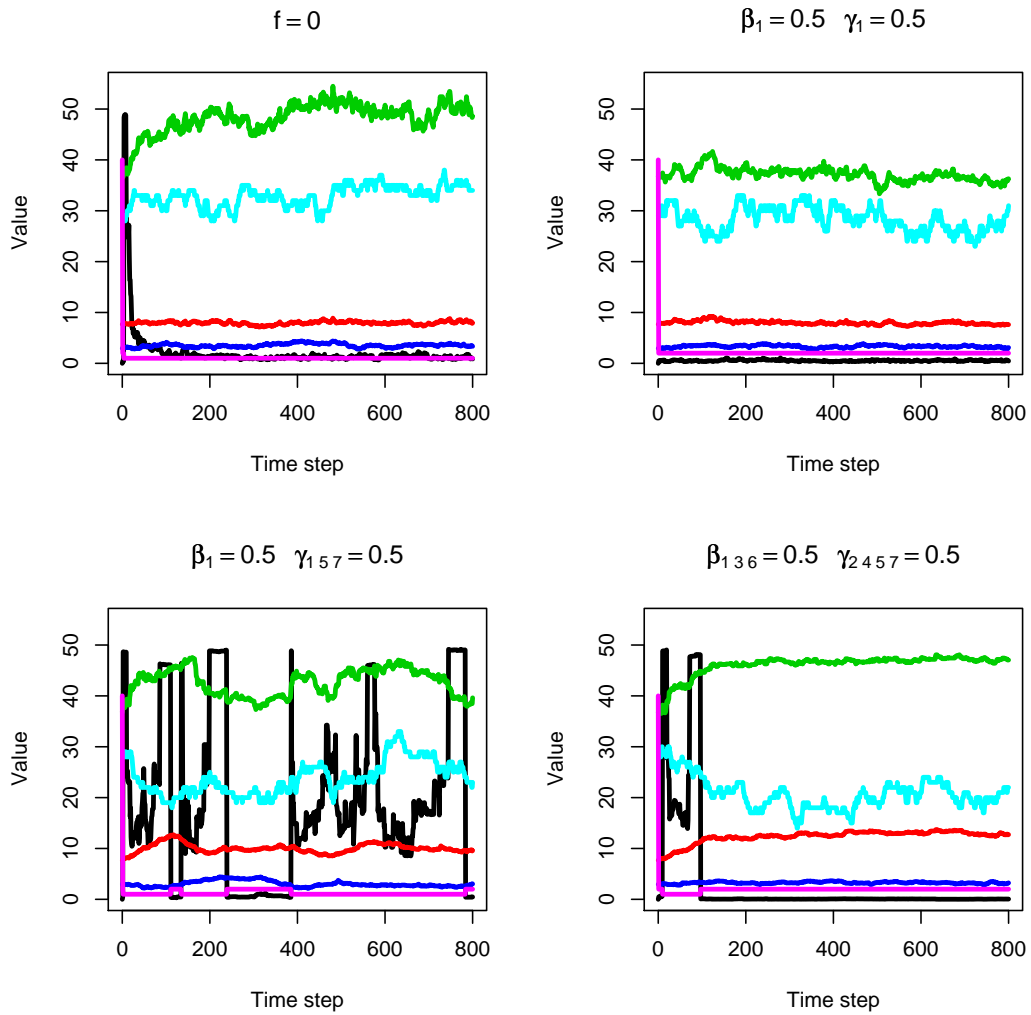
4.5 Observable aggregate output

The results of the simulation can be visualised as a congruence network after each time step. The simulation provides several dynamic views of this aggregate network of political actors:

1. A display surface with an associated two-dimensional network view. Green vertices represent governmental actors; blue vertices stand for interest groups; nodes with an oval shape represent ideology 1 and nodes with a rectangular shape ideology 2. Edges are treated as binary, and they are visualised as red lines in the graph. After each time step, the Fruchterman-Reingold layout (Fruchterman and Reingold, 1991) is updated.
2. A time series sequence of the betweenness centralisation (Freeman, 1979) of the network. This captures how homogeneously or heterogeneously the betweenness centrality values of the vertices are distributed. Betweenness centrality is a measure of importance at the vertex level. It captures on how many shortest paths between vertices a node is situated and hence whether an actor has a bridging function between coalitions or whether it is rather peripheral. Betweenness centralisation is low if there are several disconnected components or if all actors are organised in a random cloud. It is high if there is a bipolar or multipolar structure that is tied together by some vertices. For the calculation of the betweenness indices, the external Java packages JGraphT⁶ and CeMeas⁷ are employed. For the calculation of the centralisation measure, a new algorithm was written.
3. A time series sequence of the density of the network. Two new methods were written, one of which treats edges as binary and one of which takes into account edge weights. Density is the number of realised edges (or edge weights) divided by the maximum number that is possible. It is high if everyone is connected to everybody else and low if the graph is multipolar.
4. A time series sequence of the number of changed concepts in the current concept distribution. This directly measures whether a solution is in equilibrium or at least rather stable, or whether the discourse is in flux.

⁶<http://jgrapht.sourceforge.net> (as of February 26, 2010)

⁷<http://www.utdallas.edu/~axk058000/cemeas/CeMeas.html> (as of February 26, 2010)



Colors of the time series: mean concept ID, number of concept changes, betweenness centralisation, binary density, weighted density, number of disconnected components.

Figure 9: Time series outcome for several configurations of the objective functions

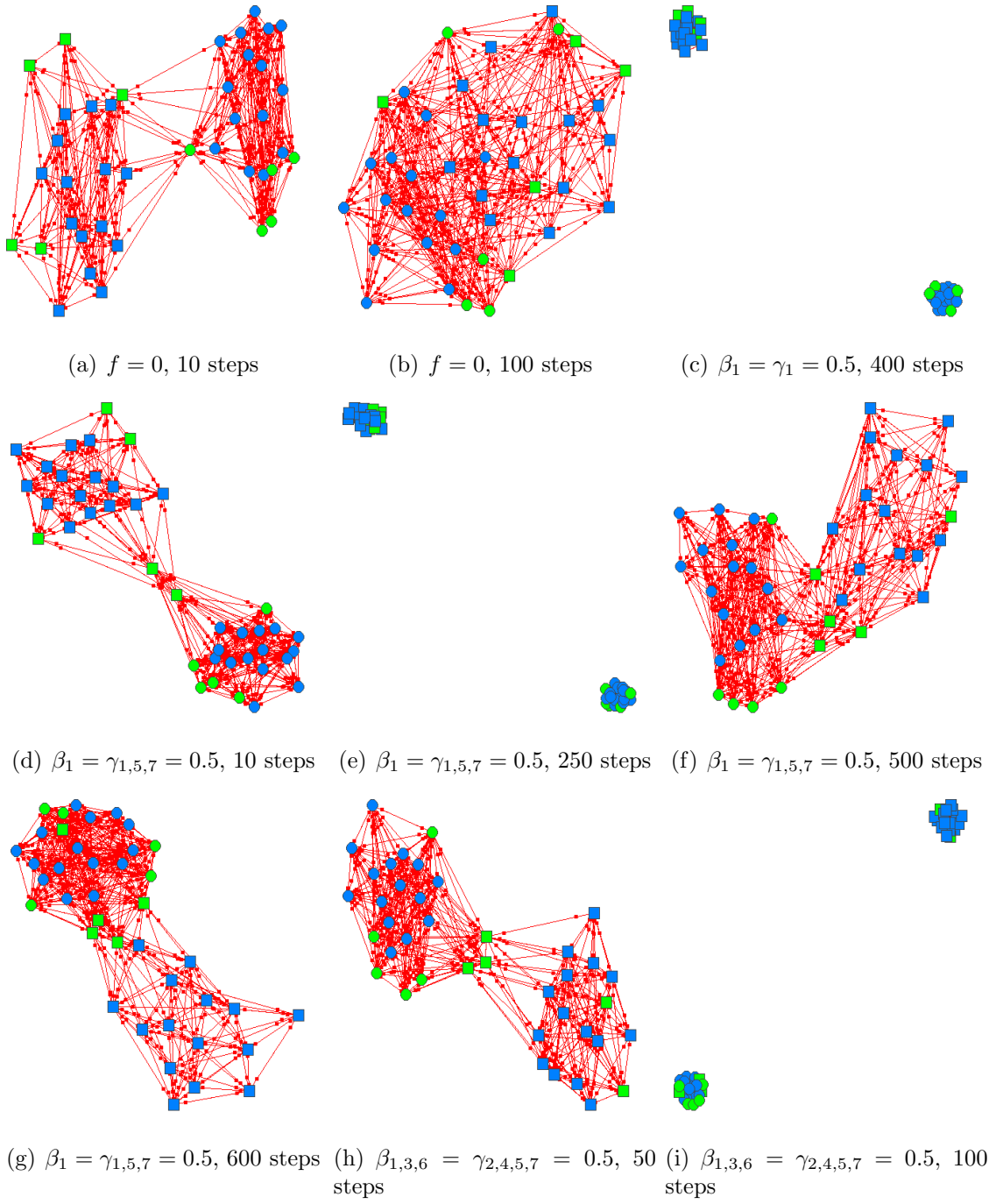


Figure 10: Network outcome

5. A sequence of the mean concept ID. As long as the number of concepts is constant and the components of the objective function are not biased, this should be more or less constant.

4.6 Preliminary results

As mentioned in section 4.4, an analysis of the results can only be tentative. The conclusions presented here are therefore limited to the purpose of illustration. This is particularly true because the results are not based on batch runs but rather on some typical cases in order to better illustrate what is happening in the model.

Figure 9 shows the time series sequences of four different configurations of the objective functions, and figure 10 presents the corresponding network views. The simulations were run over 800 time steps with 8 concepts, 5 governmental actors with ideology 1, 5 governmental actors with ideology 2, 15 interest groups with ideology 1, 15 interest groups with ideology 2, and a probability of 60 percent per round that a governmental actor makes a statement.

The most basic possibility is that none of the actors employs any of the heuristics proposed in section 4.2, i. e. all β and γ weights are set to 0. The result is a pure Erdős-Rényi random graph, i. e. edges are randomly distributed over all pairs of actors, with a uniform degree distribution. Since the graph starts off from a situation where all actors are disconnected, it takes almost 100 steps to reach an equilibrium. This is precisely what happens in the upper left part of the time series plot as well as graphs 10(a) and 10(b).

Another fairly simple model would be purely ideology-driven agents, i. e. $\beta_1 = 0.5$ and $\gamma_1 = 0.5$. The value of 0.5 is an arbitrary weight; it will be used for all instances of objective functions in this section. If actors only strive for ideological matches, the outcome should be a network where two disconnected, ideologically homogeneous components prevail. Indeed, graph 10(c) shows exactly this pattern. One can derive from the upper right time series diagram in figure 9 that this pattern is stable over all time steps.

The two basic models presented so far prove that the model produces valid output. The next two configurations will exhibit somewhat more complex patterns of interaction. In the third model, interest groups still pursue a purely ideologically oriented strategy ($\beta_1 = 0.5$), while governmental actors pursue a three-fold strategy: They take into account ideological matches ($\gamma_1 = 0.5$, like before), the current popularity of concepts ($\gamma_5 = 0.5$), and they opt for government coherence ($\gamma_7 = 0.5$). This configuration is already closer

to reality because governments indeed have a coherent line and respond to the topics raised by other actors. Yet some important factors may still be missing. The lower left part of figure 9 reveals that the number of concept changes is slightly lower than before. The most striking finding, however, is the possibility of disconnected components to join each other occasionally. Medium values of betweenness centralisation, which are quite common in this case, indicate that a couple of actors take a mediating position between the two ideological camps. Figure 10 confirms this finding: After ten steps (10(d)), some governmental actors of ideology 2 act as bridges and fulfill their task of taking median positions that is assigned to them in pluralist and corporatist polities. After 250 steps (10(e)), the two ideologies are decomposed into two components, and they join again after step 500 (10(f)). About 100 steps later (10(g)), some governmental actors of ideology 2 even join the ideology 1 cluster and leave their own ideological coalition as a homogeneous interest-group-only clique. This change, however, is reverted soon after. To sum up, the interaction of ideology, popularity and government coherence causes governmental actors to switch continuously between intermediary positions and their ideological roots. When setting γ_1 to 0, the mediation effect is more stable, and there is always a bipolar but connected structure. It should be noted that γ_5 and γ_7 cause separate components as long as they are not used together, so it is not premature to speak of an interaction effect.

A fourth configuration with even more complexity is depicted in the lower right corner of figure 9 as well as graphs 10(h) and 10(i): Interest groups go for ideological matches, concept similarity and rarity \times ideology, while governmental actors opt for history consistency, cues from similar actors, concept popularity and governmental coherence. Interestingly, this model produces similar mediation structures as the one before – but only until approximately time step 100, when two separate coalitions emerge for the rest of the time period being studied.

5 Conclusion

As always, the challenge is to bring together theories and empirical findings. How do agents decide what to contribute to the political discourse? The previous section has proposed several possible strategies that may more or less reflect reality. The simulation runs suggest that several micro factors must be combined to arrive at discursive structures that are also present in empirical cases, namely distinct coalitions which are bridged by governmental actors or parties. These coalitions may sometimes join each

other and at other times discuss issues in distinct ways, but they always return into the same political arena after a certain time period if certain conditions are met (see section 4.6). The simulation has – at least given some simplistic assumptions as featured in most formal models – shown that it is not enough to assume agents to be ideology-driven or self-consistency-maximising or peer-consistency-maximising. Only a combination of these factors yields discursive structures that are approximately comparable to the structures identified in empirical studies. Under some conditions, it is even possible to have agents occasionally switch their coalition (i. e. join the opponent) and then come back to their own coalition after some rounds, which can in rare cases even be observed in empirical cases. In any case, there is a long way to go in order to fully understand the mechanisms of political discourse. One conclusion from this paper is therefore that more attention should be paid to micro-macro linkages in political discourses. The question how discursive micro-behaviour affects the direction of a discourse deserves more attention in the literature on political discourse.

This paper started by claiming that discourse analysis usually ignores the link between actors and contents. A new methodology was introduced that may step in and close this gap. The combination of discourse analysis with social network analysis must be plausible if one acknowledges that discourse is actually a relational phenomenon which takes place among actors or between actors and concepts. Section 3 applied the discourse network framework to empirical data and demonstrated how it can be implemented in a software for qualitative content analysis. The approach was step by step applied to the issue of system change in German pension politics although the interpretations of course had to remain cursory. In addition to this empirical use of the discourse network framework, section 4 elucidated how it can be employed to theorise about political discourse. If compared to other types of text analysis, the approach has several advantages:

1. Discourse network analysis deals with both aspects of political discourse: actors and contents.
2. Discourse network analysis acknowledges that discourse can be multidimensional. It can serve as a tool to identify the dimensions or cleavage lines that are actually present in a discourse, whereas some other approaches to text analysis like the Wordscore project (Laver et al., 2003) or political claims analysis assume that discourse is one-dimensional (pro/contra, social/liberal, environment/industry, etc.). Depending on the concepts used to code the data and the scope of the actors, it

becomes possible to identify sub-topics and sub-coalitions in a policy subsystem. Political reality is complex, and discourse network analysis is a suitable tool to reduce this complexity to a degree that is interpretable by the researcher. A visualisation of a discourse network immediately reveals how each single actor or concept is embedded in the discourse. At the same time, it is possible to assess the overall topography of the discourse and identify cleavage lines and roles of actor types. Many studies provide only anecdotal evidence for the existence of adversarial coalitions and changes in their composition. Apart from using visualisations directly as explanations (Brandes et al., 2006), network-analytic methods like blockmodeling or centrality (Wasserman and Faust, 1994) can be employed to measure network properties in a more reliable and valid way. Interpretations of the networks need not necessarily be qualitative.

3. Discourse network analysis can be employed to analyse discourse over time. It allows to observe if an actor leaves a coalition and joins another coalition over time, or if a formerly united discourse is bipolarised and develops two or more distinct clusters of concepts over time. This meets the demand of policy network scholars who have called for dynamic policy network analyses for a long time (McAdam, 2003). The collection of network data is usually costly, so there have been only few longitudinal network studies. Dynamic discourse network analysis also meets the demand of scholars interested in longitudinal changes in policy ideas and learning (Hall, 1993, 290 ff.).
4. Discourse networks can be interpreted as a way of representing a discourse conceptually. This makes it compatible with both empirical and theoretical research, as shown in sections 3 and 4, respectively.
5. Discourse network analysis can be nicely combined with other policy network approaches. Methods such as QAP network regression (Krackhardt, 1988) or exponential random graph models (Robins et al., 2007) provide means to treat discursive ties as covariates of other network relations. It is thus possible to estimate the impact of preference similarity in the discourse on tie formation in policy networks if other factors are held constant.
6. Although the approach can be expressed in a formal way, it is not as reductionist as quantitative approaches because any discourse network is merely a representation of the inherent complexity of a discourse, not a reduction of this complexity.

There are also potential drawbacks, which shall not be neglected:

- Discourse network analysis requires the researcher to acquire skills in social network analysis if not already present. The costs of following the steep learning curve may be prohibitive.
- Discourse network analysis does not work automatically. One has to do a lot of manual coding before an empirical case can be analysed. The effort is comparable to qualitative content analysis, plus the effort required to do the network data analysis.
- The empirical analysis does not tell why actors choose concepts. It just shows *that* they do it. The interpretation is up to the researcher. The interpretation of a discourse network is not always easy.

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