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Brazilian Congress structural balance analysis

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Abstract

In this work, we study the behavior of Brazilian politicians and political parties with the help of clustering algorithms for signed social networks. For this purpose, we extract and analyze a collection of signed networks representing voting sessions of the lower house of Brazilian National Congress. We process all available voting data for the period between 2011 and 2016, by considering voting similarities between members of the Congress to define weighted signed links. The solutions obtained by solving Correlation Clustering (CC) problems are the basis for investigating deputies voting networks as well as questions about loyalty, leadership, coalitions, political crisis and polarization.

Keywords

Social Network; Signed Graph; Structural Balance; Correlation Clustering; Metaheuristic; Politics

I INTRODUCTION

Structural balance theory is based on the notion of cognitive consistency between friendship and hostility. For example, an enemy of a friend is probably my enemy as well, while a friend of a friend is probably my friend or can become one (Heider, 1946). In simple terms, the interaction of individuals follows the tendency to create stable (albeit not certainly conflict-free) social groups. This can be specially interesting to study similarity and correlation networks, like those originated from common voting patterns, or alliances and disputes among parties or nations (Traag and Bruggeman, 2009; Macon *et al.*, 2012; Doreian and Mrvar, 2015).

One appropriate criterion to measure the degree of balance in signed social networks is by solving the Correlation Clustering (CC) problem (Bansal *et al.*, 2002; Demaine *et al.*, 2006), which consists of partitioning a set of elements into clusters by analyzing the level of similarity between them. It aims to maximize the affinity inside each cluster (i.e. positive relationships) while, at the same time, minimizing the similarities between elements of different clusters (i.e. maximizing negative relationships).

The CC problem, which has been proved to be NP-hard (Bansal *et al.*, 2002), can be applied in several areas, such as efficient document classification (Bansal *et al.*, 2002), natural language processing (Elsner and Schudy, 2009), image segmentation (Kim *et al.*, 2014) and, of course, signed social network analysis (Doreian and Mrvar, 1996; Brusco *et al.*, 2011; Figueiredo and Moura, 2013; Levorato *et al.*, 2015). With this objective, the level of balance in a social group can be used by social network researchers to study how (and if) a group evolves to a possible balanced state.

A relaxed version of the CC problem called Symmetric Relaxed Correlation Clustering (SRCC) problem (Brusco *et al.*, 2011; Figueiredo and Moura, 2013) can also be used to evaluate balance in signed social networks. This variant, although computationally harder to solve, allows the identification of special types of social relationship, such as polarization, mediation and differential popularity (Doreian and Mrvar, 2009), originally viewed as violations of structural balance.

We implemented an algorithm known as $ILS-CC$ (Levorato *et al.*, 2015), which can efficiently solve the aforementioned problems, providing useful information for social network analysis. Using the House of Cunha website (Andrade, 2016) and the work of Mendonça *et al.* (2015) as inspiration, we provide a novel analysis of Brazilian politics inside the Chamber of Deputies (CD). In Brazil, the Chamber of Deputies (*Câmara dos Deputados*) is the lower house of the National Congress, comprised of 513 federal deputies (from 25 political parties), elected by a proportional representation of votes to serve a four-year term. Based on the CD voting records, we generate several instances of signed social networks, according to certain grouping criteria. The clustering results obtained when invoking the $ILS - CC$ procedure over these instances are the starting point of our study.

The analysis presented in this work can be applied to any network originated from voting patterns, where alliances and interest groups have strong influence.

This paper is organized as follows. Section II presents a literature review regarding Correlation Clustering problems and signed social network analysis. Section III describes the method applied to extract signed networks from the Chamber of Deputies voting data. Section IV presents an analysis of structural balance on the Chamber of Deputies voting networks, based on the solutions obtained by using our methodology. Finally, we show our conclusions in Section V.

II RELATED WORKS

Heider (1946) was the first to state Structural Balance (SB) theory in order to define sentiment relations among people belonging to the same social group (such as like/dislike, love/hate and cooperation/competitivity). Signed graphs were later applied by Cartwright and Harary (1956), formalizing SB theory which affirmed that a stabilized social group could be divided into two mutually hostile subgroups (or clusters), each having internal solidarity. Davis (1967) then proposed the more general notion of ”weak balance” or clusterable signed graph, when a balanced social group can be divided into two or more mutually antagonistic subgroups, each having internal solidarity.

When solving a clustering problem, one wants to find the most balanced partition[1] of a signed

[1] A partition is here defined as the division of the set of vertices V into non-overlapping and non-empty subsets.

graph. Using structural balance as a measure, the clustering problem is equivalent to solving the optimization problem called Correlation Clustering (CC). To our knowledge, this problem was first addressed by Doreian and Mrvar (1996) (although not under this name), who provided a heuristic solution method for analyzing structural balance on real-world social networks. Their method was implemented in software Pajek (De Nooy *et al.*, 2011). Having a document clustering problem in mind, Bansal *et al.* (2002) formalized the unweighted version of the CC problem and also discussed its NP-completeness proof. Later, Demaine *et al.* (2006) addressed the weighted version of the problem. Integer linear programming (ILP) can be used to solve the CC problem optimally (Figueiredo and Moura, 2013), but only if the number of elements is small. Since it consists of a NP-hard minimization problem, the only available solutions for larger instances are either heuristic or approximate. The solution of the CC problem and of some of its variants has already been applied in several areas, such as portfolio analysis in risk management (Harary *et al.*, 2002; Huffner *et al.*, 2009), biological systems (DasGupta *et al.*, 2007; Huffner *et al.*, 2009), grouping of genes (Bhattacharya and De, 2008), efficient document classification (Bansal *et al.*, 2002), image segmentation (Kim *et al.*, 2014) and community structure (Traag and Bruggeman, 2009).

In Yang *et al.* (2007), the CC problem is known as *community mining* and an agent-based heuristic called FEC is proposed to obtain its solution. Genetic algorithms have also been applied to document clustering, using the CC problem as objective function (Zhang *et al.*, 2008). Lately, Drummond *et al.* (2013) presented a Greedy Randomized Adaptive Search Procedure (GRASP) (Feo and Resende, 1995) implementation that provides an efficient solution to the CC problem in networks of up to 8000 vertices. Then, based on this method, Levorato *et al.* (2015) introduced sequential and parallel ILS (Iterated Local Search) (Lourenço *et al.*, 2003) procedures for the CC problem (known as $ILS - CC$), which outperformed other solution methods from the literature on three huge real-world signed social networks. Similarly to Mendonça *et al.* (2015), in this work, we will use the $ILS - CC$ algorithm to evaluate the imbalance of voting networks.

Apart from the CC problem, alternative measures to structural balance and the associated clustering problems have also been discussed in the literature. In Doreian and Mrvar (2009), the definition of a k-balanced signed graph was informally extended in order to include relevant processes (polarization, mediation, differential popularity and subgroup internal hostility) that were originally viewed as violations of structural balance. For example, the existence of a group of individuals who share only positive relationships with everyone in the network counts as imbalance in the CC Problem. Nonetheless, the individuals in this group could be identified as mediators (i.e. their relations probably won't change over time) and, as pointed in Doreian and Mrvar (2009), their relations should not be considered as a contribution to the imbalance of the network.

Using this new definition, structural balance was generalized to a version labeled as *relaxed structural balance* (Doreian and Mrvar, 2009). Similarly to the CC problem, measuring the relaxed structural balance can be accomplished through the solution to the Relaxed Correlation Clustering (RCC) problem. It is originally defined on asymmetric relations between clusters (Figueiredo and Moura, 2013); however, a redefinition of relaxed imbalance of a partition P that takes into account only symmetric relationships is also available. This gives rise to a new graph clustering problem, the Symmetric Relaxed Correlation Clustering (SRCC) Problem (Figueiredo and Moura, 2013), which will be used in this work. The SRCC problem allows us to analyze mediation processes (positive and negative). That is not the case of the RCC problem, where mediation and differential popularity cannot be pointed out.

It is worth noting that the SRCC problem is closely related with the CC problem but it is not a particular case nor is a generalization. Actually, each feasible solution (a graph partition) of the SRCC problem is also feasible in the CC problem but the problems have different cost functions, i.e., there are different ways of evaluating the imbalance of a partition. The SRCC problem is intuitively as difficult as the CC problem and is indeed a NP-hard problem (Figueiredo and Moura, 2013).

Two solution methods were initially presented in the literature for RCC problems: a greedy heuristic approach (Doreian and Mrvar, 2009) and a branch-and-bound procedure (Brusco *et al.*, 2011). Computational experiments with both procedures were reported over literature instances with up to 29 vertices and for random instances with up to 40 vertices (Doreian and Mrvar, 2009; Brusco *et al.*, 2011). We extended the ILS procedure to solve the SRCC problem, by applying additional data structures and a new objective function to evaluate the partition (Levorato *et al.*, 2017). As far as we know, the $ILS-CC$ algorithm is the only metaheuristic approach that has been used to solve RCC problems.

Previous works have employed signed graph clustering methods to analyze networks of international alliances and disputes (Traag and Bruggeman, 2009; Macon *et al.*, 2012; Doreian and Mrvar, 2015). In Levorato *et al.* (2015), by using the $ILS-CC$ algorithm, we presented a historical and geopolitical analysis of the results obtained from the voting on resolutions in the United Nations General Assembly (UNGA). Mendonça *et al.* (2015) have then applied a parallel version of the $ILS-CC$ algorithm to analyze a collection of signed networks representing voting sessions of the European Parliament. The obtained results were compared to a selection of community detection algorithms designed to process only positive links.

Several authors studied the voting behavior of politicians. As far the European Parliament (EP) is concerned, Hix (2002) evaluated different questions regarding voting behavior in the EP, including personal policy preferences, national party and European party disciplines. Afterwards, Hix and Noury (2009) compared the voting behavior of Members of the European Parliament (MEPs) in different periods, analyzing issues such as party cohesion and coalition formation.

In particular, regarding Brazil, Ames (1995) developed a model of legislative voting based on the operation of Brazil's political institutions. Mainwaring and Liñán (1997) studied party discipline in the Brazilian constitutional congress of 1987–88. Figueiredo and Limongi (2000) investigated how Brazilian presidents have succeeded by relying on the support of disciplined parties in order to get their agendas approved in the Congress. Calvão *et al.* (2015) performed an extensive analysis of data sets available for Brazilian proportional elections of legislators and city councilors throughout the period of 1970–2014, plus a comparative analysis of elections for legislative positions, in different states and years.

III NETWORK EXTRACTION

In this section, we explain the retrieval of raw voting data, and how we extracted signed networks from it.

3.1 Brazilian Chamber of Deputies

The Chamber of Deputies (CD) provides web services[2] which supply information about each of its members, including the vote cast by a specific deputy for each proposition evaluated at the CD. A deputy is described by its name, state (one of 27 Brazilian Federative Units) and political party.

For a given proposition, a deputy can express his vote in either of four ways (Câmara, 2016): *Sim* (For: the deputy wants the proposition to be accepted), *Não* (Against: s/he wants the proposition to be rejected), *Abstenção* (Abstain: s/he refuses to take part in the election and does not vote; equivalent to a white vote) and *Obstrução* (Filibuster: a form of obstruction, where debate over a proposition is extended, in order to delay or entirely prevent a vote on the proposal).

Besides the previous votes, a deputy may not vote at all, which leads to a fifth vote type: Ausência (Absent: the deputy was not present during the voting session).

The Chamber of Deputies' web services provide raw voting data, which describe the behavior of deputies apart from the others. Nonetheless, since a network is naturally relational (relationships between individuals are the product of their opinion about topics of interest), voting data has to be processed to generate the networks we wish to analyze.

3.2 Extraction algorithm

The extraction method here explained is based on the work of Mendonça *et al.* (2015). However, this procedure is being applied to Brazilian voting networks for the first time, which demanded an extension to the original algorithm, for filibuster treatment. It starts with a comparison between all pairs of deputies, analyzing the similarity of their voting choices. The obtained measures make up what is known as the agreement matrix M. Each element m_{uv} of this matrix indicates the average agreement between two deputies u and v, in other words, their level of accordance taking into consideration all propositions voted during a given time period.

While filtering the results is a relatively simple task, processing agreement scores may seriously alter the resulting network, depending on the methodology applied. Given a certain pair of deputies u and v and a proposition p_i, the proposition-wise agreement score $m_{uv}(p_i)$ is determined by comparing the votes of both deputies. It ranges from -1 if they fully disagree (one voted FOR and the other AGAINST), to +1 if they entirely agree (they share the same vote: FOR or AGAINST).

As previously stated, a voting record may contain, besides FOR and AGAINST, other values which should be equally taken into account. The first case refers to absence of one deputy or both of them (it is worth remembering that the analysis is based on pairs of deputies). The general approach is to leave out all propositions p_i that fall into this case (Porter *et al.*, 2005; Dal Maso *et al.*, 2014). Since certain deputies have low attendance rates, this might lead to distorted agreement or disagreement average scores, due to the small number of common voting sessions. To prevent this, we assume a neutral score of zero if at least one deputy is absent when voting a given proposition.

The abstention process is more complicated to understand. For example, if the political party supports a completely different view from the deputy, such pressure may be enough to lead

[2] Please visit `http://www2.camara.leg.br/transparencia/dados-abertos/dados-abertos-legislativo/webservices`

him/her to take a step towards abstention, despite the fact that s/he is FOR or AGAINST the proposition under analysis. Similarly, abstention may simply represent the deputy's neutral position when a specific topic is proposed (i.e. the deputy does not care whether or not the subject is approved). Literature provides different views to deal with ABSTAIN-FOR, ABSTAIN-AGAINST and ABSTAIN-ABSTAIN situations (Macon *et al.*, 2012; Porter *et al.*, 2005; Dal Maso *et al.*, 2014). In this work, we make use of two different ways of calculating the scores. The first one (Table 1) treats abstention as half an agreement whenever it is paired with FOR, AGAINST or other abstention, yielding a value of +0.5. In the second one (Table 2), whenever two deputies abstain at the same time, this is viewed as a full agreement (+1 value). As opposed to that, if only one abstains, a zero score is assigned, since there is not sufficient information to assert they are in agreement or disagreement. So to make things more clear, absence was not included in the tables.

The last case is filibuster (or obstruction), a vote choice specific to the Brazilian Congress, which does not occur in the European Parliament and was, therefore, not studied by Mendonça *et al.* (2015). Such practice is used to create difficulties or hindrances in a systematic way to delay or impede the approval of a bill in parliament. It is normally used by minority groups which do not have the necessary number of representatives to effectively hold back a decision taken by the majority. Therefore, any vote marked as obstruction is here regarded as AGAINST.

	FOR	ABSTAIN	AGAINST
FOR	+1	+0.5	-1
ABSTAIN	+0.5	+0.5	+0.5
AGAINST	-1	+0.5	+1

Table 1: Vote weights representing abstention as half an agreement Mendonça *et al.* (2015).

	FOR	ABSTAIN	AGAINST
FOR	+1	0	-1
ABSTAIN	0	+1	0
AGAINST	-1	0	+1

Table 2: Vote weights representing abstention as absence of opinion Mendonça *et al.* (2015).

The proposition-wise agreement score is fully specified by choosing one of the previous processing strategies. By averaging this score over all considered propositions, the average agreement can be calculated (Mendonça *et al.*, 2015). In a formal way, consider two users u and v, as well as the propositions resulting from the filtering stage: p_1, ..., p_ℓ, for which both u and v voted. The average agreement m_{uv} between these two deputies is:

$$m_{uv} = \frac{1}{\ell} \sum_{i=1}^{\ell} m_{uv}(p_i) \tag{1}$$

Similarly to the work of Mendonça *et al.* (2015), we generated one signed graph for each year (from 2011 until June 2016), taking into account all the voting sessions in that year. Graph edges with weight smaller than 0.001 were removed from the graph. The set of vertices in each signed graph represents the list of deputies who voted at least one time in the corresponding year.

IV STRUCTURAL BALANCE ANALYSIS

In this section, based on the clustering results obtained with the ILS-CC algorithm on the graphs extracted according to Section 3.2, we investigate some aspects of Brazilian politics in the Chamber of Deputies, including leadership, polarization, coalitions, loyalty and government crisis.

As explained in the previous section, we followed two approaches when generating voting networks for each year in the period between January 2011 and June 2016. We will refer to each network as either v1 or v2, depending on the strategy while dealing with abstentions:

- **v1** : abstention is worth half an agreement (+0.5), whenever it is paired with any kind of vote (FOR, AGAINST or other abstention);
- **v2** : abstention is viewed as full agreement (+1 value) only if both deputies abstain. Otherwise, if only one abstains, a zero score is assigned.

In order to improve the readability of some charts, not all party labels have been displayed. For full information, all charts and tables used in this analysis are available on-line[3].

4.1 A brief introduction to Brazilian politics

From 1994 to 2002, Brazil was governed by president Fernando Henrique Cardoso, member of the PSDB (Brazilian Social Democracy Party). In 2002, PSDB was defeated in the presidential elections by PT (Brazilian Labor Party) and president Lula da Silva was elected for a four-year term, being reelected in 2006 for one more period of four years. Then, in 2010, president Dilma Rousseff (also a PT member and supported by president Lula da Silva) won the elections, becoming the next president and, like her predecessor, was also reelected in 2014 for an additional four-year term.

Since 2013, Brazil has been facing intense political and economical crisis, aggravated by successive scandals of corruption in the heart of the government (Connors, 2016; Robins-Early, 2016). In 2016, an impeachment process was started, on charges related to breaking budget laws, and president Dilma Rousseff was turned away from her post (Watts, 2016b; BBC, 2016). However, a more detailed research over international news articles reveals different views about the root causes of the political crisis and the impeachment itself (Alston, 2016; Bevins, 2016; Connors, 2016; Leahy, 2016; Rapoza, 2016; Shahshahani and Nation, 2016; Taub, 2016).

In order to help understanding the political groups and parties referenced in the analysis, we first provide a list of the three most voted candidates and their party alliances during the presidential elections held in 2010 (Table 3) and in 2014 (Table 4). In our analysis, we will refer to the first party alliance (candidate Dilma Rousseff, in both presidential elections) as the government coalition, while the second party alliance (candidates José Serra in 2010, and Aécio Neves in 2014) will be called opposition.

Candidate	Coalition parties	#
Dilma Rousseff	PCDOB, PDT, PMDB, PR, PRB, PSB, PSC, **PT**, PTC, PTN	10
José Serra	DEM, PMN, PPS, **PSDB**, PTB, PTDOB	6
Marina Silva	**PV***	1

Table 3: Major candidates in the 2010 presidential elections, ordered by the number of votes (column # contains the number of parties). Six more candidates (from six remaining parties) ran for presidency in 2010. (*) Like PV, their parties were not in a coalition.

[3]Please visit https://public.tableau.com/profile/mario.levorato

Candidate	Coalition parties	#
Dilma Rousseff	PCDOB, PDT, PMDB, PP, PR, PRB, PROS, PSD, **PT**	9
Aécio Neves	DEM, PEN, PMN, **PSDB**, PTB, PTC, PTDOB, PTN, SD	9
Marina Silva	PHS, PPL, PPS, PRP, **PSB**, PSL	6

Table 4: Major candidates in the 2014 presidential elections, ordered by the number of votes (column # contains the number of parties). Eight more candidates (from eight remaining parties) ran for presidency in 2014. Their parties were not in a coalition.

Another useful piece of information is the list of parties according to their orientation (Table 5).

Orientation	**Parties**	**#**
Left	PCB, PCDOB, PCO, PSOL, PSTU, PT	6
Center-left	PDT, PMN, PPL, PPS, PROS, PSB, PSDB, REDE, SD	9
Center	DEM, PEN, PHS, PMB, PMDB, PRP, PSD, PSDC, PSL, PTB, PTC, PTDOB, PTN, PV	14
Center-right	NOVO, PR, PRB, PSC	4
Right	PP, PRTB	2
Total	**-**	**35**

Table 5: List of Brazilian political parties according to their orientation (Vasconcellos, 2016a,b).

Although some parties classify their orientation as center-left or center-right, a great portion of them can be regarded as center parties. As of 2016, the block known as "super-center" includes PEN, PHS, PP, PR, PRB, PROS, PSC, PSD, PSL, PTB, PTN and SD.

As mentioned in the introduction, the Chamber of Deputies (*Câmara dos Deputados*) is the lower house of the National Congress, comprised of 513 federal deputies (from 25 political parties), elected by a proportional representation of votes to serve a four-year term. Table 6 displays the number of elected deputies from each party/coalition, for the 2010 (2011-2014 term) and 2014 elections (2015-2018 term).

4.2 Methodology

We attempt to identify groups of deputies (and their respective parties) in the Chamber of Deputies signed networks, generated based on voting session records publicly made available by the open data initiative of the Brazilian Government [4].

To do so, we apply the $ILS - CC$ (Levorato *et al.*, 2015) procedure to solve the two problems introduced in Section II: the Correlation Clustering (CC) problem and the Symmetric Relaxed Correlation Clustering (SRCC) problem. The procedure changes the objective function that evaluates the clustering partition accordingly.

However, based on the obtained results, we chose to rely our analysis solely on SRCC clustering results [5]. The reason is that all CC solutions presented only one or two clusters as output, which, to our knowledge, did not accurately represent the political groups in the Chamber of Deputies. One possible explanation is that, as stated in Section II, when compared to the SRCC problem,

[4] The data services of the Brazilian Chamber of Deputies website can be found at `http://www2.camara.leg.br/transparencia/dados-abertos`

[5] We solved the SRCC problem by fixing the number of clusters (k) in the solution to $k = 4$, so as to reflect the number of coalition groups: the three main coalitions in each four-year term, listed in Tables 3 and 4, plus an additional group to represent all the candidates / parties not in a coalition.

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the CC problem tends to over-evaluate the imbalance of a network, for penalizing relationships associated, for instance, with mediation processes.

Next we present several clustering results that help answering interesting questions concerning political dynamics. Each question and its respective analysis is organized in a subsection.

Remark that, whenever a clustering result is displayed as a treemap, each cluster is marked with a different color and corresponding cluster label (begins with letter C). Besides, for each cluster, the treemap displays the sum of deputies (in parenthesis), grouped by their respective party.[6] Since the clustering is based on deputies, political parties may be split into different clusters.

4.3 Evaluation of the loyalty of parties from the same coalition

We have extracted a table which, for each year, coalition and party (columns *Year*, *Party Alliance* and *Party*, respectively), gives details about the percentage of deputies from each party in each cluster (columns *C1* to *C4*). This way it is possible to spot if the majority of the deputies of a specific party does not belong to the most populous coalition cluster, which constitutes a strong evidence that such party is unfaithful to its coalition. By using this data, one can verify that, for example, in 2011 (Table 7), only 41% of PDT, 38% of PR and 42% of PRB deputies were classified inside the largest ruling coalition cluster, formed by 206 deputies. In 2012 (Table 8), only 16% (3 in 19) of PSC deputies accompanied the biggest government group, comprised of 237 deputies. Finally, in 2014 (on both network versions), just half of PT and PDT deputies followed the government coalition (see column *C1* in Table 9).

4.4 Evolution of the support of the government coalition

We start by analyzing two tables that provide, for each year and network version (columns *Year* and *Version*, respectively), the number of deputies according to their respective party alliance and the cluster to which they belong (columns *Party Alliance* and columns *C1* to *C4*, respectively). The first table (Table 10) refers to the period from 2011 to 2014 (54th legislature of the Chamber of Deputies), while the second one (Table 11) gives information about the years of 2015 and 2016 (55th legislature, corresponding to president Dilma Rousseff's second presidential term).

We observe that, in the first year of president Dilma Rousseff's government (2011), the government coalition is divided, roughly speaking, in two or three big groups, depending on the network version on which the analysis is based. According to version v1 (Figure 1), the largest cluster (C1) has 64% of the allied deputies. Also, the great majority of the president's party (PT), 82 deputies, are to be found in this cluster.

From 2012 onwards, a clear basis consolidation can be observed, with 77% of the allied deputies in the same group (cluster C1 in Figure 2). This cluster also holds more than 80 deputies of president's party (PT).

In 2013 (Figure 3), the percentage of allied deputies inside the largest cluster (C1) rises to 82% of the coalition (74 PT deputies). However, in 2014 (the last year of president Dilma Rousseff's first term), a change of course comes about. This measure falls to 66% (Figure 4) and, even worse, only about half of PT's deputies are inside the main coalition group (C3).

[6] Due to space limitation, it is not possible to show the cluster label for all groups/squares in the Figure. Please visit the website `https://public.tableau.com/profile/mario.levorato` to access the interactive version of the plots with full information.

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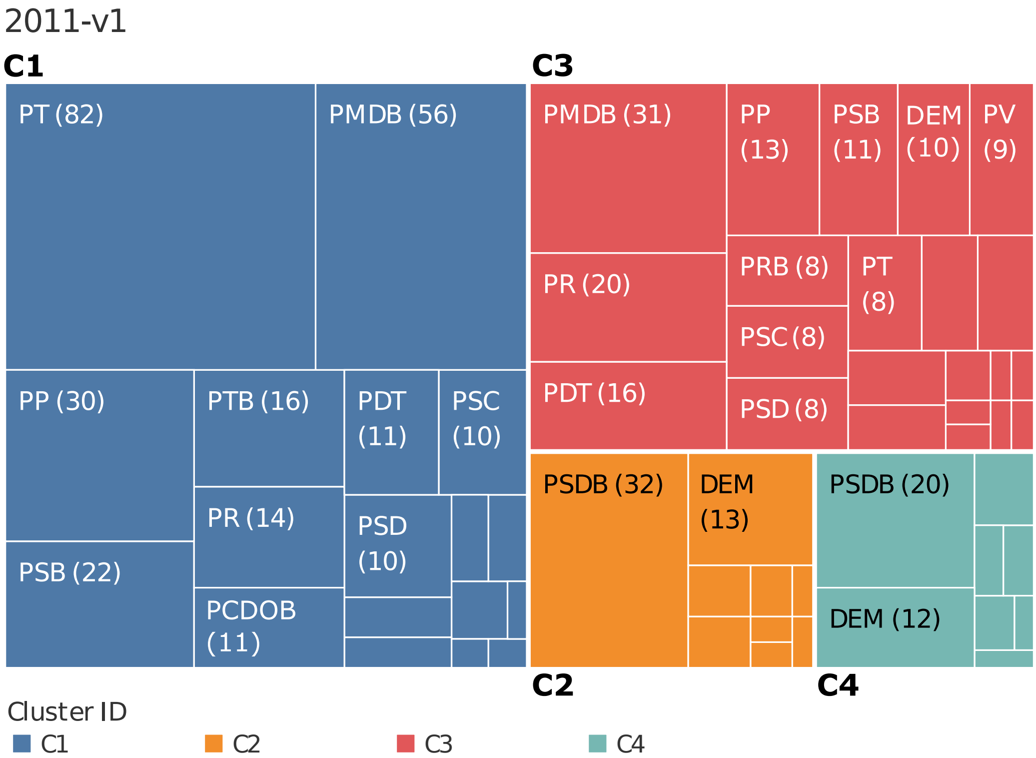

Figure 1: SRCC clustering results for the year of 2011, when solving version v1 of the voting network, by fixing the number of clusters in the solution to $k = 4$.

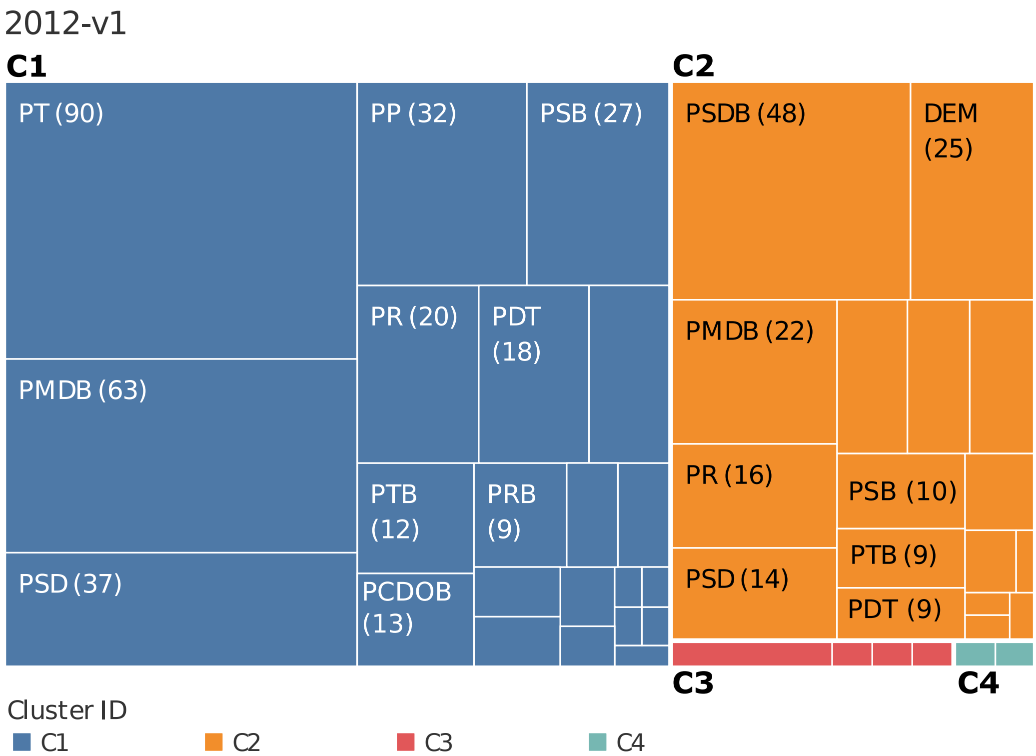

Figure 2: SRCC clustering results for the year of 2012, when using version v1 of the voting network, by fixing the number of clusters in the solution to $k = 4$.

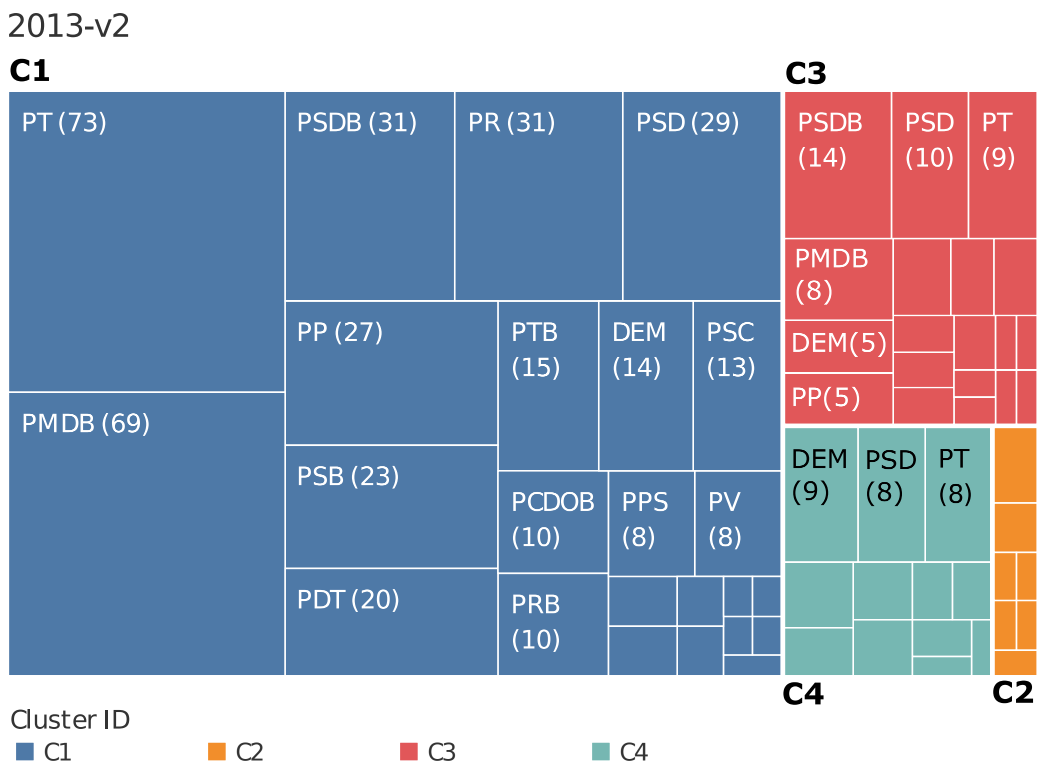

Figure 3: SRCC clustering results for the year of 2013, when using version v2 of the voting network, by fixing the number of clusters in the solution to $k = 4$.

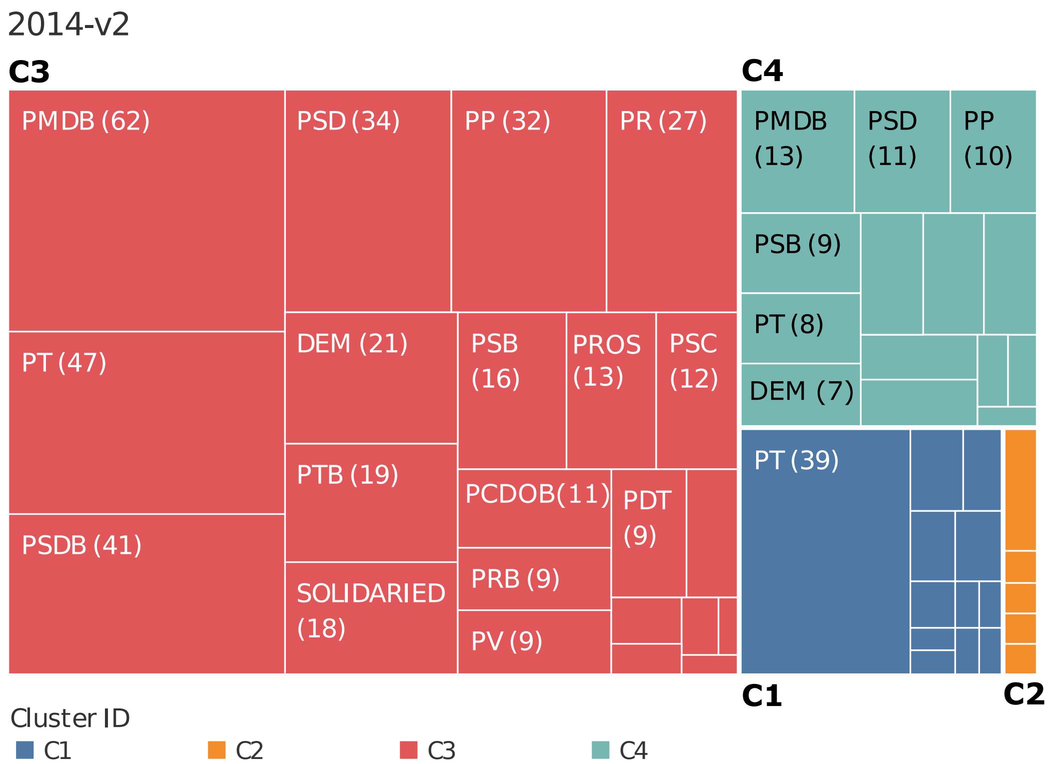

Figure 4: SRCC clustering results for the year of 2014, when using version v2 of the voting network, by fixing the number of clusters in the solution to $k = 4$.

A close look at president Dilma Rousseff's second presidential term is surprising. In 2015, the biggest group of what should be the government's new coalition (cluster C1 in Figure 5) is formed by 70% of the total number of deputies of the coalition as a whole. Notwithstanding, this group houses at most 10 deputies of the president's party (PT). Consider as well that the greatest part of PT deputies is in fact isolated in a smaller cluster, together with a few deputies from less influential parties. Note that both network versions show almost identical results[7].

A similar picture takes place in 2016 (Figure 6), when about two thirds of the supposedly allied deputies belong to the same group, which contains only 11 PT deputies. Similarly, 50 PT deputies can be found in another cluster.

Briefly speaking, results point out that in the years of 2015 and 2016, even though there are still large groups in which most deputies are from the so-called government coalition, such groups are no longer in accordance with the president's party, which is perfectly understandable because of the political crisis and the loss of parliamentary support, news widely broadcast (Dyer, 2015; Boadle, 2016; Watts, 2016a).

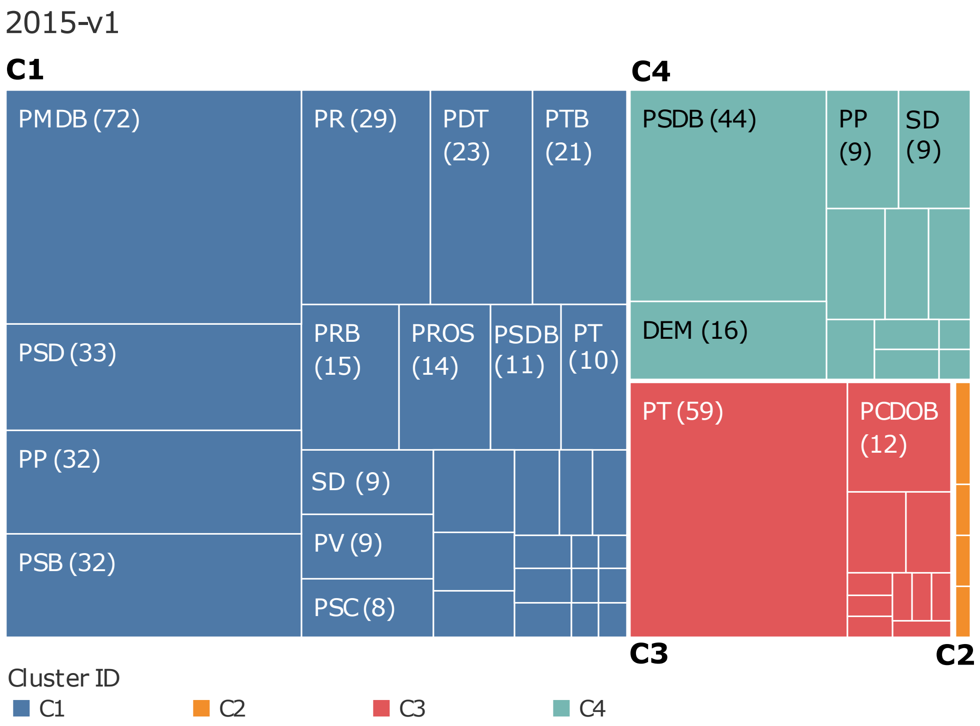

Figure 5: SRCC clustering results for the year of 2015, when using version v1 of the voting network, by fixing the number of clusters in the solution to $k = 4$.

4.5 Strength of party leadership

This study was carried out as follows: for each year from 2011 to 2016 and for each party, we scanned data about the deputies and the clusters from which they make part. This information was then cross-referenced with the cluster where the leader of the respective party is found. This way it is possible to have a clear view of how strong the leadership of each party is: if a specific deputy belongs to different cluster than its party leader, on average, this deputy did not vote the way his party expected. The full results with the information about the deputies classified

[7] Please visit https://public.tableau.com/profile/mario.levorato for a full list of charts and tables.

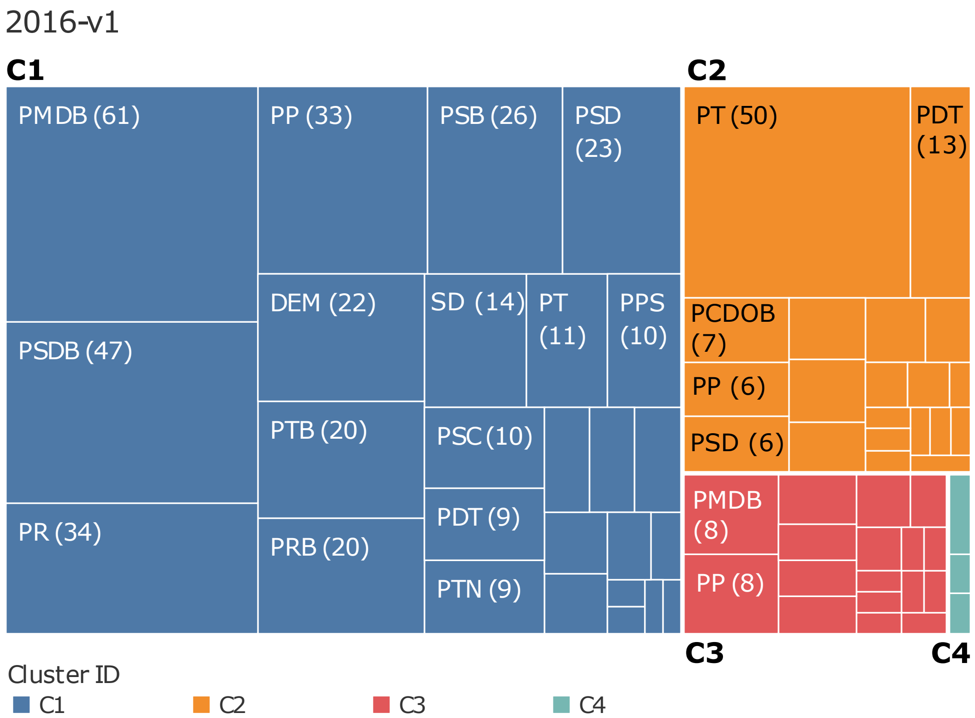

Figure 6: SRCC clustering results for the year of 2016, when using version v1 of the voting network, by fixing the number of clusters in the solution to $k = 4$.

in the same cluster as their respective party leader (percentage) are available in Table 12 for 2011-2014 and in Table 13 for 2015-2016.

For each year, the following parties have been identified as having low percentage ($\rho < 50\%$) of deputies who vote after their party leaders, independently of the analyzed network version:

- 2011: PRB, PRP, PSC, PSD;
- 2012: PR, PSB, PSC, PSD, PTB, PV;
- 2013: PCDOB, PRP, PV;
- 2014: PCDOB, PDT;
- 2015: PSC;
- 2016: PCDOB, PMB, PSL, PTDOB.

Deep consideration into this list will reveal that, as we spot a considerably great number of deputies arranged in clusters where their party leaders are not present, there is strong evidence that, on average, voting recommendations from party leaders have not been followed by many deputies.

4.6 The split of the government ruling party when the Brazilian political crisis began

The clustering results for 2014 strongly suggest that president Dilma Rousseff's party (PT) split, with 47 deputies in the first cluster, 39 in the second and 8 in the third. As seen on Figure 4, the treemap shows the fragmentation of PT in the last year of the president's first term.

4.7 Government coalition's loss of support after president Dilma Rousseff's reelection

According to the results obtained by the ILS-CC algorithm, in 2015, after president Dilma Rousseff's reelection, three clusters cover 99% of the deputies (Figure 5). The parties inside each cluster reveal the main political groups at that time:

- the largest group includes mainly center parties, such as the majority of PMDB, PSD, PP and PR;
- the second biggest group is formed by opposition parties like PSDB and DEM;
- the last one represents the government core parties, such as PT (59 deputies) and PCDOB (12 members).

A comparison between 2015 and previous years (see Figures 1, 2 and 5) reveals that the government coalition has gone through a substantial loss of support, mostly from center parties. These results anticipate a movement which became clear only the following year, when PMDB and other center-parties voted to leave the governing coalition (Boadle, 2016; Watts, 2016a; Barchfield and Savarese, 2016).

4.8 Center parties moved towards opposition when the government coalition lost power

Looking at the data for the years of 2015 (Figure 5) and 2016 (Figure 6), one can observe that the majority of center party and opposition deputies started sharing the same group. There was a strong approximation between PMDB (center), PSDB and DEM (opposition), which have previously been in separate clusters. According to the charts, one can notice that center parties have moved towards opposition.

In 2015, there was a large movement of parties from the government coalition, which went to a "super-centered" group. These parties include: PROS (12), PRB (12), PDT (22), PR (25), PP (28), PSD (33) and PMDB (71).

In 2016, the following coalition parties have effectively migrated to what can be interpreted as a huge opposition cluster: PDT(17), PRB (20), PSD (21), PP (30), PR (33) and PMDB (56).

News broadcast confirm this movement: first, the approximation between Brazil's biggest party (PMDB) and PSDB was reported (Gonçalves, 2016; Sambo and Godoy, 2016). Shortly after, PMDB voted to leave the governing alliance (Boadle, 2016; Watts, 2016a), followed by three other parties (PDT, PRB and PP) (Barchfield and Savarese, 2016).

4.9 Polarization between political groups

In 2012 (on both network versions), the chamber of deputies is polarized in two large groups (see Figure 2). The first one with 238 members, led by the majority of PT and PMDB deputies (government base). The other cluster is mainly characterized by opposition parties, such as PSDB and DEM, but it also includes dissidents from center parties like PMDB and PSD.

4.10 Relative imbalance of the analyzed signed social networks

Several authors have mentioned that real-world signed social networks are more balanced than expected (Kunegis *et al.*, 2009; Leskovec *et al.*, 2010; Kunegis *et al.*, 2010; Facchetti *et al.*, 2011). As seen on Table 14, the signed social networks generated from the Brazilian CD voting data are in fact highly balanced, which supports existing research about that topic.

V CONCLUDING REMARKS

In this article, we have investigated some of the aspects inherent to signed voting networks and political relationships, by using data from the Brazilian Chamber of Deputies (CD). We have first extracted a collection of networks based on voting patterns of the CD members. We have then applied a clustering algorithm specifically designed for signed networks, called $ILS-CC$, which aims to improve structural balance.

The clustering results allowed us to gather evidence that certain parties are indeed unfaithful to their coalition. Besides, the obtained data perfectly confirms the news broadcast about the Brazilian political situation, such as the loss of support that government coalition experienced.

Equally, the algorithm has proved to be a useful tool to spot parties under weak leadership and the existence of polarization between two large political groups. Our analysis also confirmed that the signed social networks we generated from the Brazilian CD voting data are indeed extremely balanced, hence supporting previous related works.

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2010

Coalition	Party	
Dilma Rousseff (Government)	PDT	28
	PMDB	79
	PR	41
	PRB	8
	PSB	34
	PSC	17
	PT	88
	Total	**295**
Jose Serra (Opposition)	DEM	43
	PPS	12
	PSDB	54
	PTB	21
	Total	**130**
Marina Silva	PV	15
	Total	**15**
Not in a coalition	PCdoB	15
	PHS	2
	PP	41
	PSOL	3
	PTdoB	4
	Other parties	8
	Total	**73**
Total		513

2014

Coalition.	Party	
Dilma Rousseff (Government)	PCdoB	10
	PDT	19
	PMDB	66
	PP	37
	PR	34
	PRB	21
	PROS	11
	PSD	36
	PT	70
	Total	**304**
Aecio Neves (Opposition)	DEM	22
	PSDB	54
	PTB	25
	PTdoB	1
	SD	15
	Total	**117**
Marina Silva	PHS	5
	PPS	10
	PSB	34
	Total	**49**
Not in a coalition	PSC	13
	PSOL	5
	PV	8
	Other parties	17
	Total	**43**
Total		513

Table 6: Number of elected deputies from each party and coalition, for the 2010 elections (2011-2014 term, on the left) and for the 2014 elections (2015-2018 term, on the right).

Year	Version	Party Alliance	Party	C1	C2	C3	C4	Total
				Cluster ID				
2011	v2	Government	PDT	41.38% 12	6.90% 2	27.59% 8	24.14% 7	100.00% 29
			PMDB	67.42% 60	2.25% 2	12.36% 11	17.98% 16	100.00% 89
			PR	37.84% 14	8.11% 3	18.92% 7	35.14% 13	100.00% 37
			PRB	41.67% 5		33.33% 4	25.00% 3	100.00% 12
			PSB	64.71% 22	2.94% 1	14.71% 5	17.65% 6	100.00% 34
			PSC	61.11% 11		22.22% 4	16.67% 3	100.00% 18
			PT	91.11% 82		5.56% 5	3.33% 3	100.00% 90
			PTC				100.00% 1	100.00% 1
			Total	66.45% 206	2.58% 8	14.19% 44	16.77% 52	100.00% 310
		Opposition	DEM	7.89% 3	68.42% 26	7.89% 3	15.79% 6	100.00% 38
			PMN	75.00% 3		25.00% 1		100.00% 4
			PPS		58.33% 7	25.00% 3	16.67% 2	100.00% 12
			PSDB	1.72% 1	91.38% 53	3.45% 2	3.45% 2	100.00% 58
			PTB	72.73% 16		13.64% 3	13.64% 3	100.00% 22
			Total	17.16% 23	64.18% 86	8.96% 12	9.70% 13	100.00% 134
		Total		51.58% 229	21.17% 94	12.61% 56	14.64% 65	100.00% 444

Table 7: Party coalition and clustering details for the year of 2011, when solving version v2 of the voting network, by fixing the number of clusters in the solution to $k = 4$. For each coalition (column Party Alliance) and for each party (column Party), each cell shows the percentage of deputies of that party inside each cluster (columns C1 to C4).

Year	Version	Party Alliance	Party	Cluster ID C1	C2	C3	C4	Total
2012	v2	Government	PDT	60.71% 17	3.57% 1	10.71% 3	25.00% 7	100.00% 28
			PMDB	80.23% 69		10.47% 9	9.30% 8	100.00% 86
			PR	61.11% 22		19.44% 7	19.44% 7	100.00% 36
			PRB	90.00% 9		10.00% 1		100.00% 10
			PSB	81.08% 30		13.51% 5	5.41% 2	100.00% 37
			PSC	15.79% 3		36.84% 7	47.37% 9	100.00% 19
			PT	92.47% 86	1.08% 1	4.30% 4	2.15% 2	100.00% 93
			PTC	100.00% 1				100.00% 1
			Total	**76.45% 237**	**0.65% 2**	**11.61% 36**	**11.29% 35**	100.00% 310
		Opposition	DEM	16.67% 5		43.33% 13	40.00% 12	100.00% 30
			PMN	100.00% 2				100.00% 2
			PPS	18.18% 2		63.64% 7	18.18% 2	100.00% 11
			PSDB	5.36% 3	7.14% 4	48.21% 27	39.29% 22	100.00% 56
			PTB	57.14% 12		14.29% 3	28.57% 6	100.00% 21
			Total	**20.00% 24**	**3.33% 4**	**41.67% 50**	**35.00% 42**	100.00% 120
		Total		60.70% 261	1.40% 6	20.00% 86	17.91% 77	100.00% 430

Table 8: Party coalition and clustering details for the year of 2012, when solving version v2 of the voting network, by fixing the number of clusters in the solution to $k = 4$. For each coalition (column Party Alliance) and for each party (column Party), each cell shows the percentage of deputies of that party inside each cluster (columns C1 to C4).

Year	Version	Party Alliance	Party	Cluster ID C1	C2	C3	C4	Total
2014	v2	Government	PDT	10.53% 2	5.26% 1	47.37% 9	36.84% 7	100.00% 19
			PMDB	1.25% 1	5.00% 4	77.50% 62	16.25% 13	100.00% 80
			PR			81.82% 27	18.18% 6	100.00% 33
			PRB	10.00% 1		90.00% 9		100.00% 10
			PSB	3.85% 1		61.54% 16	34.62% 9	100.00% 26
			PSC		6.67% 1	80.00% 12	13.33% 2	100.00% 15
			PT	41.49% 39		50.00% 47	8.51% 8	100.00% 94
			Total	**15.88% 44**	**2.17% 6**	**65.70% 182**	**16.25% 45**	**100.00% 277**
		Opposition	DEM			75.00% 21	25.00% 7	100.00% 28
			PMN			66.67% 2	33.33% 1	100.00% 3
			PPS	11.11% 1		66.67% 6	22.22% 2	100.00% 9
			PSDB	2.04% 1		83.67% 41	14.29% 7	100.00% 49
			PTB		5.00% 1	95.00% 19		100.00% 20
			Total	**1.83% 2**	**0.92% 1**	**81.65% 89**	**15.60% 17**	**100.00% 109**
		Total		**11.92% 46**	**1.81% 7**	**70.21% 271**	**16.06% 62**	**100.00% 386**

Table 9: Party coalition and clustering details for the year of 2014, when solving version v2 of the voting network, by fixing the number of clusters in the solution to $k = 4$. For each coalition (column Party Alliance) and for each party (column Party), each cell shows the percentage of deputies of that party inside each cluster (columns C1 to C4).

Coalition Loyalty 2011-2014

Year	Version	Party Alliance	Cluster ID C1	C2	C3	C4	Total
2011	v1	Government	199 64.19%	4 1.29%	103 33.23%	4 1.29%	**310** **100.00%**
		Opposition	22 16.42%	48 35.82%	28 20.90%	36 26.87%	**134** **100.00%**
	v2	Government	206 66.45%	8 2.58%	44 14.19%	52 16.77%	**310** **100.00%**
		Opposition	23 17.16%	86 64.18%	12 8.96%	13 9.70%	**134** **100.00%**
2012	v1	Government	238 76.77%	68 21.94%	2 0.65%	2 0.65%	**310** **100.00%**
		Opposition	27 22.50%	89 74.17%	4 3.33%		**120** **100.00%**
	v2	Government	237 76.45%	2 0.65%	36 11.61%	35 11.29%	**310** **100.00%**
		Opposition	24 20.00%	4 3.33%	50 41.67%	42 35.00%	**120** **100.00%**
2013	v1	Government	132 44.59%	2 0.68%	158 53.38%	4 1.35%	**296** **100.00%**
		Opposition	64 57.66%		46 41.44%	1 0.90%	**111** **100.00%**
	v2	Government	239 82.13%	6 2.06%	28 9.62%	18 6.19%	**291** **100.00%**
		Opposition	70 65.42%	1 0.93%	22 20.56%	14 13.08%	**107** **100.00%**
2014	v1	Government	196 70.76%	6 2.17%	41 14.80%	34 12.27%	**277** **100.00%**
		Opposition	98 89.91%	1 0.92%	2 1.83%	8 7.34%	**109** **100.00%**
	v2	Government	44 15.88%	6 2.17%	182 65.70%	45 16.25%	**277** **100.00%**
		Opposition	2 1.83%	1 0.92%	89 81.65%	17 15.60%	**109** **100.00%**

Table 10: Party coalition during the 2010 presidential elections, for the 2011-2014 term. For each year (column *Year*) and network version (column *Version*), the table shows the number of deputies in each party alliance (column *Party Alliance*) found in each cluster (columns *C1* to *C4*). Results obtained when fixing the number of clusters in the solution to $k = 4$.

Coalition Loyalty 2015-2016

Year	Version	Party Alliance	Cluster ID C1	C2	C3	C4	Total
2015	v1	Government	229 69.60%	3 0.91%	82 24.92%	15 4.56%	329 100.00%
		Opposition	49 41.88%		3 2.56%	65 55.56%	117 100.00%
	v2	Government	210 63.83%	3 0.91%	95 28.88%	21 6.38%	329 100.00%
		Opposition	28 23.93%		7 5.98%	82 70.09%	117 100.00%
2016	v1	Government	201 63.41%	89 28.08%	23 7.26%	4 1.26%	317 100.00%
		Opposition	104 86.67%	7 5.83%	9 7.50%		120 100.00%
	v2	Government	23 7.26%	92 29.02%	186 58.68%	16 5.05%	317 100.00%
		Opposition	11 9.17%	8 6.67%	88 73.33%	13 10.84%	120 100.00%

Table 11: Party coalition during the 2014 presidential elections, for the 2015-2018 term. For each year (column *Year*) and network version (column *Version*), the table shows the number of deputies in each party alliance (column *Party Alliance*) found in each cluster (columns *C1* to *C4*). Results obtained when fixing the number of clusters in the solution to $k = 4$.

Party Leadership (2011-2014)

Party	2011 v1	2011 v2	2012 v1	2012 v2	2013 v1	2013 v2	2014 v1	2014 v2
DEM	34%	68%	83%	40%	69%	32%	89%	75%
PCDOB	73%	80%	100%	100%	23%	23%	27%	27%
PDT	55%	28%	64%	25%	44%	80%	21%	47%
PMDB	63%	67%	73%	80%	42%	82%	81%	78%
PMN					67%	67%	100%	33%
PP	67%	67%	82%	90%	31%	75%	91%	74%
PPS	33%	58%	64%	18%	55%	73%	89%	22%
PR	54%	35%	44%	19%	62%	84%	88%	82%
PRB	33%	42%	90%	90%	90%	100%	10%	90%
PROS					100%	100%	67%	62%
PRP	50%	50%			50%	50%	100%	100%
PSB			27%	14%	70%	85%	88%	62%
PSC	44%	17%	47%	47%	53%	11%	73%	80%
PSD	35%	17%	27%	18%	35%	59%	79%	71%
PSDB	34%	91%	86%	48%	65%	6%	92%	84%
PSOL	33%	67%	100%	100%	67%	67%	100%	100%
PT	91%	91%	97%	92%	62%	81%	51%	50%
PTB	73%	73%	43%	29%	68%	88%	85%	95%
PTDOB	75%	75%	100%	67%	67%	100%	100%	100%
PV	75%	33%	50%	40%	50%	20%	89%	100%

Table 12: For each party (column *Party*), displays the percentage of its deputies who vote after their party leader (i.e. deputies classified in the same group of their party leader), for each year between 2011 and 2014 (columns *2011* to *2014*) and for each network version (columns *v1* and *v2*). On certain periods, the numbers associated with a party may not have been shown. Either because the party still did not exist at that time or did not have any representation in parliament at all.

Party Leadership (2015-2016)

	Year / Version			
	2015		2016	
Party	v1	v2	v1	v2
DEM	30%	96%	85%	77%
PCDOB	92%	92%	50%	50%
PDT	100%	96%	59%	64%
PEN	100%	100%	75%	75%
PHS	100%	100%	100%	100%
PMB			14%	14%
PMDB	96%	95%	11%	77%
PP	78%	68%	69%	4%
PPS	58%	75%	100%	100%
PR	83%	71%	83%	80%
PRB	75%	40%	100%	100%
PROS	100%	86%	71%	71%
PRP			100%	100%
PSB	94%	68%	79%	61%
PSC	46%	43%	71%	71%
PSD	89%	89%	70%	64%
PSDB	80%	96%	87%	2%
PSL			25%	25%
PSOL	100%	100%	100%	100%
PT	83%	89%	82%	82%
PTB	81%	69%	95%	81%
PTDOB	100%	50%	50%	50%
PTN	75%	25%	82%	18%
PV	90%	20%	67%	67%
REDE	100%	100%	80%	80%

Table 13: For each party (column *Party*), displays the percentage of its deputies who vote after their party leader (i.e. deputies classified in the same group of their party leader), for the years of 2015 and 2016 (columns *2015* and *2016*; until June 2016) and for each network version (columns *v1* and *v2*). On certain periods, the numbers associated with a party may not have been shown. Either because the party still did not exist at that time or did not have any representation in parliament at all.

Year	2010		2011		2012		2013	
Version	v1	v2	v1	v2	v1	v2	v1	v2
$\%SRI(P)$	0.25%	0.26%	0.38%	0.43%	0.34%	0.33%	0.31%	0.35%
Year	**2014**		**2015**		**2016**			
Version	v1	v2	v1	v2	v1	v2		
$\%SRI(P)$	0.07%	0.07%	0.39%	0.40%	1.92%	2.32%		

Table 14: Symmetric Relaxed Imbalance ($\%SRI(P)$) measure obtained with the solution of the SRCC problem over the CD signed graphs, according to year and network version.