

Scaling models in political science

Introduction

To make positive assessments of the positions of political actors, political scientists have developed, refined and borrowed tools to measure the relative positions of political actors on dimensions of politics.

Where do parties or voters stand on the left–right spectrum? What policies define it? Is left–right really

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the most salient dimension in a political system? To answer these questions, so-called ‘scaling models’ have been developed to estimate the positions of actors on the basis of their observable behaviors. To this end, many data sources have been explored: from voting behavior in parliament (Poole & Rosenthal, 1985) to party manifestos (Budge, 2001), parliamentary speech (Lauderdale & Herzog, 2016) and positions in social media networks (Barberá, 2015). This contribution gives an insight into how this has been achieved, a brief introduction to the math behind it and an overview of their applications, both technical and substantive. We close with some criticisms of these methods, which speak to the development of further validation methods.

Dimensional reduction and politics

The making of political decisions is a complex process of selecting issues, formulating positions on them, publicly communicating these, and making, adopting and implementing policy. What issues are relevant for often binary voting choices is not a priori given but aggregated by political actors such as parties, legislators or political entrepreneurs to produce cohesive policy platforms that allow direct comparison. These ‘dimensions’ of politics allow complex multidimensional spaces to be reduced to simple vote choices and offer some solution to the information dilemma of democracy.

To answer these questions, it is necessary to develop measurements for the positions of actors on different dimensions. The ‘spatial’ interpretation is very intuitive to voters and political scientists alike. To voters, spatial understandings of politics are a powerful metaphor, in which parties serve an aggregative function for informational reduction and policymaking across a multitude of issues. Faced with at times many party platforms, voters consider parties’ positions relative to their own on a limited number of dimensions or substantive issues. This notion of spatial modeling has its origins in the translation of geospatial to preferential proximity in economics (Hotelling, 1929). Such theorizing of preferential proximity between political actors has led to powerful concepts such as the Median Voter Theorem (Black, 1948) and Downsian Spatial Voting theories (Downs, 1957).

But where do voters or parties stand and what policy issues define these positions? These are crucial questions for studying many themes of keen interest to political scientists.

Traditional dimensions

One way of doing this is the a priori definition of what is important for politics, such as analyzing the left–right spectrum. Traditionally, in most Western societies, the left–right spectrum reflects positions on state intervention into the economy. However, other dimensions such as cultural values, cosmopolitanism versus nation state, liberal versus conservative or even integration into the European Union matter most for decision making (Kriesi et al., 2008).

All these dimensions can be measured using expert surveys (Polk et al., 2017), where scholars sort parties along defined axes. This is comparable to self-placement in general population surveys. Respondents are asked where they stand on the spectrum from one to ten. Of course, this measure depends on respondents knowing the substantial meaning of the spectrum. We can then think of these as relative positions based on voter estimates of party placements along common dimensions. This is not always clear, since not all political systems are defined by a single dimension, and what indicates these positions varies between contexts.

Inductive recovering of dimension

As an alternative, the question of what constitutes the most important differences in political orientation can be derived *inductively*, ex post (Benoit & Laver, 2012). Such models are called unsupervised, as they require no human input as to the substance of the dimension and autonomously discover and scale positions on the underlying dimensions, which explain most differences in the data.

Whether from votes, responses, political language or even social media behavior, using mathematical algorithms to identify the most important differences is a well-established idea in political science. These approaches attempt to explain the largest amount of difference from the minimal number of dimensions. Here we already see the analogy to information aggregation in substantive political terms. A statistical analogy is the use of factor analysis to identify correlated items to measure latent, underlying constructs. They allow turning individual decisions across items into scales, which differentiate types of correlated behavior. This ‘scaling’ applies to any given behavior and allows clustering individuals along a common dimension. We attempt to identify clusters of behavior over individuals that allow us to describe them as similar or different based on these important dimensions.

There are two classes of algorithms that allow reducing dimensions: ‘parametric’ and ‘non-parametric’. Non-parametric approaches usually apply singular value decomposition (SVD) to decompose a matrix representing individuals and nominal data on some behavior of interest. Factor analysis, correspondence analysis and multidimensional scaling all belong to this group.

The second class are algorithms from ‘Item-Response-Theory’, using *maximum-likelihood* or *Bayesian* methods to iterate over all combinations of individual and behavior to fit all coefficients simultaneously. The result is an explicit modeling of estimation errors, but they are computationally intensive and thus take considerably more time to estimate. In reality, these algorithms all describe the similarity of the actors and their behavior simultaneously. What this behavior is and therefore represents depends on the behavior used for scaling. In other words, any matrix of behavioral units can allow us to position actors in n -dimensional space, where n is the number of decisions they all decide on. This very general approach lets us apply these methods to numerous behavioral traces so long as we have comparable count data.

What to scale

Traditionally, roll-call votes (RCVs; Poole & Rosenthal, 1985) are used as a way to derive ideology from voting behavior. In party-centered systems, the absence of informative RCVs leads to a stronger focus on alternative sources such as political text produced by political parties or individual legislators (Beauchamp, 2012). Social media have become important data sources for these endeavors, as they exist in most political contexts and involve most political actors. Behavior on social media is also individuated and, in contrast to parliamentary speeches, less likely to be affected by institutional provisions (Castanho Silva & Proksch, 2021; Ceron, 2017). Two main data sources can be exploited on social media: the social network – that is, the interconnection between the accounts – and the text entailed in the posts and/or comments. The next section will give a brief overview of how to estimate policy positions using each of these data sources.

Behavior

For US legislators, a popular application for measuring policy positions has been through RCVs. The underlying argument is that by voting

in costly elections in Congress, legislators reveal their preferences on each proposal. Knowing how each legislator voted on each proposal allows us to derive central dimensions of conflict. The NOMINATE (or Nominal Three-Step Estimation) is a multidimensional scaling application for RCVs developed by Poole and Rosenthal (1985). NOMINATE has gone through many iterations: Dynamic (Poole & Rosenthal, 2001), Weighted or Dynamic-Weighted (Carroll et al., 2009) and more recently alpha, a fully Bayesian, Markov Chain Monte Carlo-based version of the original implementation (Carroll et al., 2013).

While there are significant technical differences between these versions of the NOMINATE scaling technique, they all rely on the same fundamental assumptions. Political choice data, in this case nominal legislative voting data, can be projected to low-dimensional Euclidean spaces. Positions are revealed on broader dimensions as voting is a function of the legislators’ ideology or ideal-point; this allows us to (1) make positive statements on legislator positions and (2) predict voting in subsequent roll calls.

The innovation of NOMINATE shows that ideal points of preference can be recovered from observing political choices. RCV is just one type of behavior we can look at; there are many more. One variant of NOMINATE that has proven influential is PAC-NOMINATE, where interest groups are treated like legislators who make binary choices regarding the candidates and campaigns they do or do not finance (McCarty et al., 2006). However, a far more popular implementation of deriving positions from campaign finance data is Bonica’s (2014) DIME+ (Database on Ideology, Money in Politics and Elections), which recovers ideal points not just for incumbents but also candidates, donors and interest groups alike.

While positioning legislators and candidates is valuable itself, it is often necessary to put voters and politicians on the same scale. One approach exploits the fact that politicians and citizens are increasingly using social media as a platform for news consumption and political engagement, most notably via Twitter. Given the structure of Twitter as a network of followers and followings, we can use these as binary-choice data to infer the positions of political actors. The most prominent application of this was developed by Pablo Barberá (2015), in which a Bayesian Spatial Model was implemented based on similarities in the followings of social media users. Assuming that social networks are homophilic, then ‘birds of the same feather Tweet together’. Barberá’s model fits

additional controls for the popularity of accounts. Given that party leaders and government officials are more likely to be followed by those who do not politically agree with them, this can be accounted for using Bayes's Theorem.

Indeed, actionable behaviors such as RCV and campaign finance are informative of preference, but these have limited transferability to other contexts where we might lack appropriate data, and in the case of many parliamentary systems, RCV is not informative of individual position. Instead, exploring how political rhetoric differs by ideology has been a recent focus of political scientists.

Text as data

Where roll-call votes and campaign finance are not feasible, automatic text scaling is a promising measurement strategy for ideological positions. Using textual sources has many advantages: text is abundant and provides extremely rich detail that can be leveraged in the measure. In addition, textual documents, such as social media posts or parliamentary speeches, are supposedly individual behaviors and thus well-designed data sources to measure individual ideological position. It is very intuitive to understand that to get a sense of the ideological position of Boris Johnson or Angela Merkel, their speeches will provide a much more fine-grained picture than their voting behavior.

Still, scaling automatically and systematically based on text has proven to be challenging in many ways. For instance, most words are very rarely used and cannot be automatically linked with a given position. On the other hand, the most frequent words (*stopwords*) are likely mere noise and do not inform about a specific position. In addition, many words are *polysemic* – they endorse a different meaning depending on the context – and will even signal different positions depending on the context. For instance, words such as liberty, taxes or immigration can all be used to signal both left-leaning and right-leaning position. There are many possible steps that can be taken in preprocessing text data, whether this involves removing number, punctuation, compounding multi-word expressions or stemming words, or removing words based on commonality or rarity. All the possible combinations of these steps will likely affect the results of our model (Denny & Spirling, 2018).

Finally, word choices are shaped by many factors that are independent of the policy position. Scaling models are word-choice models: they model word frequencies as a function of ideological positions. Unsupervised models deployed for

these contexts often assume that the principal dimension structuring word choices is the left–right spectrum. But, when writing a text, authors are influenced by many more factors: the topic of the debate, their mood, their audience. These factors create noise that needs to be filtered out of the estimation to ensure its accuracy. Here again, models are associated with different data sources.

Manifestos

The assumption that party competition was driven by issue emphasis, and therefore allowed parties to be positioned based on these issues, led to the emergence of the Comparative Manifestos Project (CMP) (Budget et al., 2001). In a gigantic effort, the issue emphasis of each manifesto sentence was coded for numerous political systems across time. These qualitative evaluations can easily be transposed to quantitative measures of issue count data by manifestos, splitting codes into left–right categories and scaling by taking the count of right minus the count of left, divided by the total counts. Many alternative methods have been proposed to offer more grounded estimates, such as ignoring the overall length and taking the relative proportional difference (right count – left count / left count – right count) (Kim & Fording, 2002), or scaling based on the log odds-ratios (Lowe et al., 2011). However, coding issue content is an extensive and expensive task, and not all manifestos can be coded (Bräuninger et al., 2012).

Algorithms can help to overcome this issue and estimate the position of manifestos at lower cost. Benoit and Laver (2003) propose Wordscores, which identifies the left–right spectrum using anchor texts (for applications, see Bräuninger et al., 2020; Bräuninger & Giger, 2018; Gross & Debus, 2018; Gross & Jankowski, 2020; Kosmidis et al., 2019). Based on the word counts of the two anchor texts that define the ends of the scales, words are given scores based on their discriminating power. Then out-of-sample texts can be estimated by taking a weighted average of their relative word counts and the word scores. Slapin and Proksch (2008) developed a fully unsupervised method, Wordfish, that does not require any anchor text and used it to accurately scale German party manifestos. To do so, Wordfish jointly estimates the position as well as their relationship with the word counts and assumes that the principal dimension structuring word choices is the left–right spectrum (for applications, see Catalinac, 2016; Ceron 2012, 2014; Greene & Haber, 2016; Louwerse, 2011).

Parliamentary speeches

Parliamentary speeches are one of the primary data sources when estimating the position of individual politicians. They have been analyzed using both Wordscores (Bäck & Debus, 2016; Herzog & Benoit, 2015; Slapin et al., 2018) and Wordfish (Arzheimer, 2015; Baumann et al., 2015; Klüver, 2013; Louwerse, 2012; Proksch & Slapin, 2010). When using unsupervised models, speeches should be carefully considered because the recovered dimension can be misleading. Lauderdale and Herzog (2016) demonstrate that debates in the Irish *Dail* are primarily structured around the government–opposition divide rather than along the left–right spectrum. To mitigate this problem, they propose Wordshoals, which takes the debate structure into account and estimates a Wordfish position for each debate and then represents these positions in a low-dimensional space through Bayesian estimation.

At least two further structural aspects can bias the scaling of parliamentary speeches: agenda setting (Slapin & Proksch, 2009) and the selection of speakers (Bäck et al., 2014). Finally, a very promising method targets the specific issue of polysemic words. Rheault and Cochrane (2020) take advantage of word-embedding techniques to incorporate the context in their estimations. Using *neural networks*, they model the choice of a specific word as a function of both its context (defined as the six words appearing around the modeled word) and the author. In doing so, they provide some control for the context and can distinguish between the left-leaning and right-leaning meaning of terms. Similarly, Watanabe (2021) introduces Latent Semantic Scaling, which provides a semi-supervised text scaling approach. Based on a given context character (and its synonyms), a fitted word window and two sets of seed words (positive/negative), word embeddings can be derived from an associative model and document positions recovered based on reciprocal averaging.

Social media

Inherently political language like manifestos and speeches is recently complemented by a new form of expression for politicians: social media. In comparison it is noisy, unstructured and not necessarily political; but it is also free, unmediated and free of selection biases often encountered in parliament. Boireau (2014) and Ceron (2017) first apply traditional scaling models (Wordfish) to this new text form and show meaningful differences on political axes. Temporão et al. (2018) show the validity of

these positions by comparing them to voting advice applications and Barberá's ideal-point method. Sältzer (2020) shows that they represent a meaningful political space, even inside political parties, making social media a promising data source for positioning individuals. More recently, Ebanks et al. (2021) have shown that networks of retweets among US senators and factor analysis of joint sentiment-topics discussed on social media derive similar positions in policy space.

Criticism and validation

While scaling positions has become a staple method in political science, its application is not without valid criticism.

Meaning

Both ex ante and ex post interpretations have been criticized for not accurately relating to political conflict. Ex ante dimensions can impose a bias to the data, as scholars base their observation in other sources, which are potentially subjective and outdated.

For instance, one common critique of expert surveys such as Chapel Hill (CHES) is the relative invariance of the survey over time. On the other hand, automated scaling measures often recover dimensions that only loosely represent what we would expect as scholars to be the main dimension of conflict. Depending on the data source, the data-generating process can introduce non-observed bias, such as agenda setting or an exogenous shock, which leads to confusing non-ideological differences with ideological ones. The most accepted applications in both approaches seem to be those that produce both 'face validity' and 'convergent validity'. Converging indicators is not evidence for validity if all indicators suffer from the same biases. In addition, as ideology is a moving target, specific measures could grow inaccurate and miss important shifts. For this reason, the robust and objective validation of scaling models is crucial.

Validity

Face validity is an implicit form of criterion validity: is the measure behaving in a way we would expect? This, of course, is a trade-off with the ability to measure unexpected changes. Often, long-term established measures such as NOMINATE are used to validate newer methods. However, it is often impossible to make an argument of an improved scaling technique if credibility is

weighted against external validation of past metrics. For scaling models, there exist approaches for statistical validity, such as perplexity measures or the explained variation. However, those are often uninformative about what the dimensions really mean. For text models, the concept of semantic validity has recently been introduced to see whether the terms that define positions on dimensions actually relate to what we would expect to be the substantive policy content of underlying dimensions (Chan & Sältzer, 2020; Chang et al., 2009).

Continuity

A third major criticism lies in the question of metrics. Scales are by definition continuous. Traditional evaluations of correct classification, such as the ability to correctly predict the class of a text, are categorical in nature. This makes computing criterion validity difficult, as scales exist based on comparisons. Pairwise comparison is a promising way to tackle this issue. Instead of assigning a numeric score to individual cases, documents or authors are iteratively compared one to another. Coders must state for each pair of cases which one holds the most left-leaning or right-leaning position. The pairwise comparisons can then be modeled using a Bradley-Terry model, which allows estimating an ideological score. Comparing pairs of documents takes longer because each document has to be compared many times to be scaled precisely, but the task is considerably easier for human coders, and thus more reliable, than direct scaling on a numeric scale. Breunig, Guinaudeau and Roth (2021) asked young political leaders to compare pairs of German MPs. This new measurement strategy comes close to what could be a gold standard for an ideological measure within a specific context. It is certainly not the last measure to be developed, but this non-behavioral measure can now be used to validate behavioral measures and understand when speeches, roll-call votes or social media can be used to estimate ideological position. The scope of pairwise comparisons only depends on the compared documents. If MPs from different countries are compared, they could then be scaled in one single continuum.

DANIEL BRABY, BENJAMIN GUINAUDEAU AND
MARIUS SÄLTZER

Related entries

Digital parties; Machine learning and deep learning; Sentiment analysis and opinion mining; Text as data; Topic models

References

- Arzheimer, K. (2015). The AfD: Finally a successful right-wing populist Eurosceptic party for Germany. *West European Politics*, 38(3), 535–556.
- Bäck, H., & Debus, M. (2016). *Political Parties, Parliaments and Legislative Speechmaking*. Palgrave Macmillan.
- Bäck, H., Debus, M., & Müller, J. (2014). Who takes the parliamentary floor? The role of gender in speech-making in the Swedish Riksdag. *Political Research Quarterly*, 67(3), 504–518.
- Barberá, P. (2015). Birds of the same feather tweet together: Bayesian ideal point estimation using Twitter data. *Political Analysis*, 23(1), 76–91.
- Baumann, M., Debus, M., & Müller, J. (2015). Convictions and signals in parliamentary speeches: Dáil Éireann debates on abortion in 2001 and 2013. *Irish Political Studies*, 30(2), 199–219.
- Beauchamp, N. (2012). *Using Text to Scale Legislatures with Uninformative Voting*. New York University Mimeo.
- Benoit, K., & Laver, M. (2003). Estimating Irish party policy positions using computer wordscore: The 2002 election – A research note. *Irish Political Studies*, 18(1), 97–107.
- Benoit, K., & Laver, M. (2012). The dimensionality of political space: Epistemological and methodological considerations. *European Union Politics*, 13(2), 194–218.
- Black, D. (1948). On the rationale of group decision-making. *Journal of Political Economy*, 56(1), 23–34.
- Boireau, M. (2014). Determining political stances from Twitter timelines: The Belgian parliament case. In *Proceedings of the 2014 Conference on Electronic Governance and Open Society: Challenges in Eurasia* (pp. 145–151). Association for Computing Machinery.
- Bonica, A. (2014). Mapping the ideological marketplace. *American Journal of Political Science*, 58(2), 367–386.
- Bräuninger, T., & Giger, N. (2018). Strategic ambiguity of party positions in multi-party competition. *Political Science Research and Methods*, 6(3), 527–548.
- Bräuninger, T., Debus, M., & Müller, J. (2012). *Parteienwettbewerb in den deutschen Bundesländern*. 1st ed. VS Verlag.
- Bräuninger, T., Debus, M., Müller, J., & Stecker, C. (2020). *Parteienwettbewerb in den deutschen Bundesländern*. 2nd ed. VS Verlag für Sozialwissenschaften.
- Breunig, C., Guinaudeau, B., & Roth, S. (2021). Measuring legislators' ideological position using pairwise-comparisons. Working paper.
- Budge, I. (2001). Validating party policy placements. *British Journal of Political Science*, 31(1), 179–223.
- Carroll, R., Lewis, J. B., Lo, J., Poole, K. T., & Rosenthal, H. (2009). Comparing NOMINATE and IDEAL: Points of difference and Monte Carlo tests. *Legislative Studies Quarterly*, 34, 555–591.
- Carroll, R., Lewis, J. B., Lo, J., Poole, K. T., & Rosenthal, H. (2013). The structure of utility in spatial

DANIEL BRABY, BENJAMIN GUINAUDEAU AND MARIUS SÄLTZER

- models of voting. *American Journal of Political Science*, 57(4), 1008–1028.
- Castanho Silva, B., & Proksch, S. (2021). Politicians unleashed? Political communication on Twitter and in parliament in Western Europe. *Political Science Research and Methods*, 1–17. DOI: 10.1017/psrm.2021.36.
- Catalinac, A. (2016). From pork to policy: The rise of programmatic campaigning in Japanese elections. *The Journal of Politics*, 78(1), 1–18.
- Ceron, A. (2012). Bounded oligarchy: How and when factions constrain leaders in party position-taking. *Electoral Studies*, 31(4), 689–701.
- Ceron, A. (2014). Gamson rule not for all: Patterns of portfolio allocation among Italian party factions. *European Journal of Political Research*, 53(1), 180–199.
- Ceron, A. (2017). Intra-party politics in 140 characters. *Party Politics*, 23(1), 7–17.
- Chan, C. et al. (2020). oolong: An R package for validating automated content analysis tools. *Journal of Open Source Software*, 5(55), 2461.
- Chang, J., Gerrish, S., Wang, C., Boyd-Graber, J. L., & Blei, D. M. (2009). Reading tea leaves: How humans interpret topic models. *Advances in Neural Information Processing Systems* (pp. 288–296). Neural Information Processing Systems.
- Denny, M., & Spirling, A. (2018). Text preprocessing for unsupervised learning: Why it matters, when it misleads, and what to do about it. *Political Analysis*, 26(2), 168–189.
- Downs, A. (1957). An economic theory of political action in a democracy. *Journal of Political Economy*, 65(2), 135–150.
- Ebanks, D., Yan, H., Alvarez, R. M., Das, S., & Sinclair, B. (2021). Legislative communication and power: Measuring leadership from social media data. *APSA Preprints*. DOI: 10.33774/apsa-2021-m4wls.
- Greene, Z., & Haber, M. (2016). Leadership competition and disagreement at party national congresses. *British Journal of Political Science*, 46(3), 611–632.
- Gross, M., & Debus, M. (2018). Does EU regional policy increase parties' support for European integration. *West European Politics*, 41(3), 594–614.
- Gross, M., & Jankowski, M. (2020). Dimensions of political conflict and party positions in multi-level democracies: Evidence from the Local Manifesto Project. *West European Politics*, 43(1), 74–101.
- Herzog, A., & Benoit, K. (2015). The most unkindest cuts: Speaker selection and expressed government dissent during economic crisis. *The Journal of Politics*, 77(4), 1157–1175.
- Hotelling, H. (1929). Stability in competition. *The Economic Journal*, 39(153), 41–57.
- Hotelling, H. (1990). Stability in competition. In A. C. Darnell (Ed.), *The Collected Economics Articles of Harold Hotelling* (pp. 50–63). Springer.
- Kim, H., & Fording, R.C. (2002). Government partisanship in Western democracies, 1945–1998. *European Journal of Political Research*, 41(2), 187–206.
- Klüver, H. (2013). *Lobbying in the European Union: Interest Groups, Lobbying Coalitions, and Policy Change*. Oxford University Press.
- Kosmidis, S., Hobolt, S. B., Molloy, E., & Whitefield, S. (2019). Party competition and emotive rhetoric. *Comparative Political Studies*, 52(6), 811–837.
- Kriesi, H., Grande, E., Lachat, R., Dolezal, M., Bornschier, S., & Frey, T. (2008). *West European Politics in the Age of Globalization*. Cambridge University Press.
- Lauderdale, B. E., & Herzog, A. (2016). Measuring political positions from legislative speech. *Political Analysis*, 24(3), 374–394.
- Louwerse, T. (2011). The spatial approach to the party mandate. *Parliamentary Affairs*, 64(3), 425–447.
- Louwerse, T. (2012). Mechanisms of issue congruence: The Democratic Party mandate. *West European Politics*, 35(6), 1249–1271.
- Lowe, W., Benoit, K., Mikhaylov, S., & Laver, M. (2011). Scaling policy preferences from coded political texts. *Legislative Studies Quarterly*, 36(10), 123–155.
- McCarty, N., Poole, K. T., & Rosenthal, H. (2006). *Polarized America: The Dance of Political Ideology and Unequal Riches*. MIT Press.
- Polk, J., Rovny, J., Bakker, R., Edwards, E., Hooghe, L., Jolly, S., Koedam, J., Kostelka, F., Marks, G., Schumacher, G., Steenbergen, M., Vachudova, M., & Zilovic, M. (2017). Explaining the salience of anti-elitism and reducing political corruption for political parties in Europe with the 2014 Chapel Hill Expert Survey data. *Research & Politics*. DOI: 10.1177/2053168016686915.
- Poole, K. T., & Rosenthal, H. (1985). A spatial model for legislative roll call analysis. *American Journal of Political Science*, 29(2), 357–384.
- Poole, K. T., & Rosenthal, H. (2001). D-Nominate after 10 years: A comparative update to congress – A political-economic history of roll-call voting. *Legislative Studies Quarterly*, 26(1), 5. DOI: 10.2307/440401.
- Proksch, S.-O., & Slapin, J. B. (2009). How to avoid pitfalls in statistical analysis of political texts: The case of Germany. *German Politics*, 18(3), 323–344.
- Proksch, S.-O., & Slapin, J. B. (2010). Position taking in European Parliament speeches. *British Journal of Political Science*, 40(3), 587–611.
- Rheault, L., & Cochrane, C. (2020). Word embeddings for the analysis of ideological placement in parliamentary corpora. *Political Analysis*, 28(1), 112–133.
- Sältzer, M. (2020). Finding the bird's wings: Dimensions of factional conflict on Twitter. *Party Politics*. DOI: 10.1177/1354068820957960.
- Slapin, J. B., & Proksch, S.-O. (2008). A scaling model for estimating time-series party positions from texts. *American Journal of Political Science*, 52(3), 705–722.
- Slapin, J. B., Kirkland, J. H., & Lazzaro, J., Leslie, P., & O'Grady, T. (2018). Ideology, grandstanding, and strategic party disloyalty in the British parliament. *American Political Science Review*, 112(1), 15–30.

- Temporão, M., Vande Kerckhove, C., van der Linden, C., Dufresne, Y., & Hendrickx, J. M. (2018). Ideological scaling of social media users: A dynamic lexicon approach. *Political Analysis*, 26(4), 457–473.
- Watanabe, K. (2021). Latent semantic scaling: A semi-supervised text analysis technique for new domains and languages. *Communication Methods and Measures*, 15(2), 81–102.