Speaking out or speaking in? Changes in political rhetoric over time

When standing for election, politicians often position themselves as "outsiders", promising to shake up the status quo. But once elected, do "outsiders" become "insiders"? **Iliyan R. Iliev**, **Xin Huang** and **Yulia R. Gel** search for clues through the analysis of political rhetoric

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It is election time in the United States. President Donald Trump is running for a second term, while Joe Biden, vice-president to Barack Obama, is hoping to stop him. The details are different, but the dynamics of the race could almost be a rerun of 2016: the political outsider (Trump) versus the career politician (Biden; and before him, Clinton). The "outsider" versus "insider" dynamic is apparent from the tone of each candidate's campaign, the way each man acts, and in what they say and the way they say it.

This dynamic is by no means unique to recent presidential campaigns. Recent elections for the US Congress have seen many candidates positioning themselves as outsiders, promising to bring a "breath of fresh air" to an otherwise "stale institution". "The Squad" – a quartet of US congresswomen – is an example of this. Alexandria Ocasio-Cortez of New York, Ilhan Omar of Minnesota, Ayanna Pressley of Massachusetts, and Rashida Tlaib of Michigan are all women of colour and under 50 years of age, demographic categories that are underrepresented in the legislature. They advocate progressive policies and are sometimes at odds with their own party, the Democrats, in what they say and what they do.

But do "outsiders" remain "outsiders" once elected to office? More specifically, does their political rhetoric – the things they say – change over time as they become more immersed in the institutions of government?

Political speech

To investigate this question, we developed an approach that would first analyse legislative speech at a particular point in time, then look for common features and group legislators together based on those common features.[1] Then, for subsequent time periods, we would rerun this analysis and clustering, to see whether groupings of legislators changed and whether the number of groups increased or decreased over time. If groupings became larger and fewer, this would be evidence for politicians becoming more similar in their political speech. If groups became smaller and more numerous, this would be evidence for politicians becoming more divergent.

For this analysis, we chose to focus on the Senate, and particularly senators who were members of the Senate Committee on Energy and Natural Resources between the years 2001 and 2011. We gathered together more than 40,000 individual statements from hearings of the Committee during that time period, which are publicly available from the US Government Printing Office. The statements of interest are the individual rhetoric of senators, and they were extracted from the hearings using a Java algorithm, separating their statements from other statements such as testimonies from witnesses and speeches by foreign delegations.

To process the senators' statements, we modified a supervised learning approach originally developed by Hopkins and King.[2] The algorithm was trained using a subset of 947 statements from our complete data set, with each statement hand-coded into one of four distinct categories: "pro-lobby" (in support of the predominant energy interests), "neutral", "procedural", and "anti-lobby" (in opposition to the predominant energy interests).

For illustrative purposes, consider two statements from a single politician, Senator Jeff Bingaman, who was a Democratic senator for New Mexico from 1983 to 2013. On 3 February 2005, Bingaman said: "any serious effort to reduce the demand for new oil, the increased demand for oil over the next decade or two will have to have as a central component reducing the demand in the transportation sector … policies that would encourage or facilitate generation of electricity from sources other than natural gas would be helpful in reducing the future demand for natural gas." This statement would be hand-coded as "anti-lobby". A month later, on 3 March 2005, Bingaman said: "oil and gas research and development programs are slated for termination. That seems short-sighted to me. Some of that work is done in our state at New Mexico Tech. It's work that's intended to help independent petroleum producers get maximum production off of wells in this country." This statement would be hand-coded as "pro-lobby".[3]

To make sure that the algorithm had been trained correctly, we performed a check known as five-fold cross-validation, which allows us to compare the output of the machine coding to the output of the hand coding. The training data was randomly partitioned into five groups, and the algorithm was then trained on four parts, while the remaining partition was used to test the misclassification rate – that is, the error rate of the procedure. The resulting accuracy score (i.e., the proportion of correctly ▶

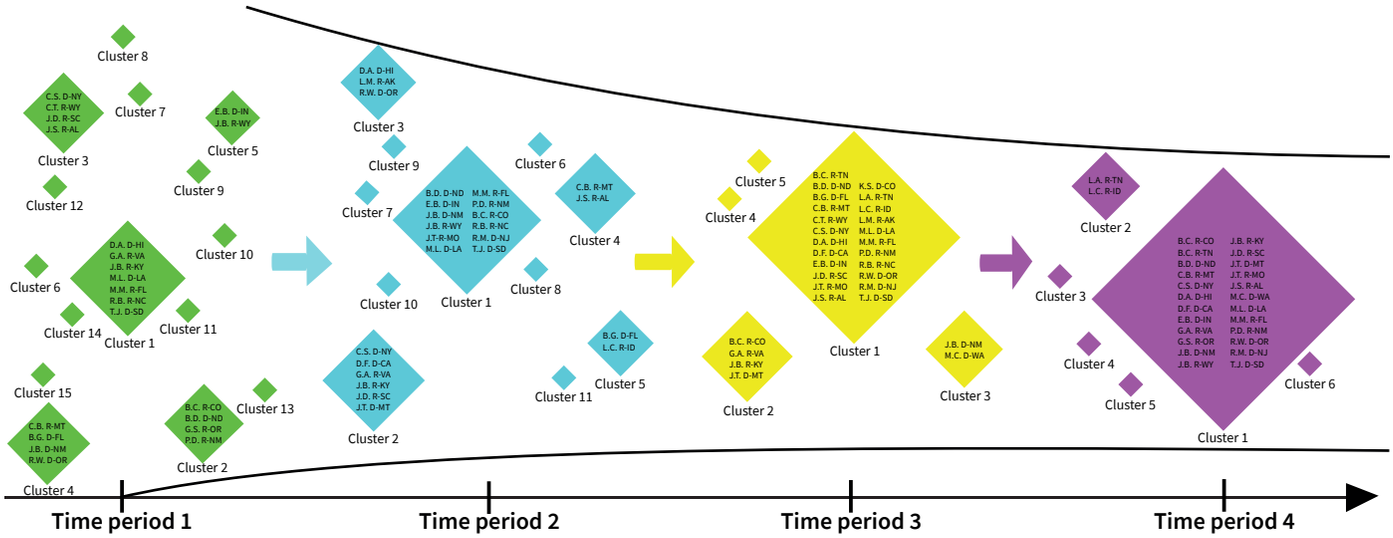

Figure 1: Dynamic clustering of legislative rhetoric in the full membership data set. Calinski–Harabasz (CH) scores – an internal measure of cluster validity based on the average between- and within-cluster sum of squares – are 9.41, 6.14, 5.02 and 0.95 for time periods 1, 2, 3 and 4, respectively. These CH scores indicate that later periods tend to require fewer clusters to achieve a lower CH score and, hence, better partitioning of the data into homogeneous groups of legislative rhetoric.

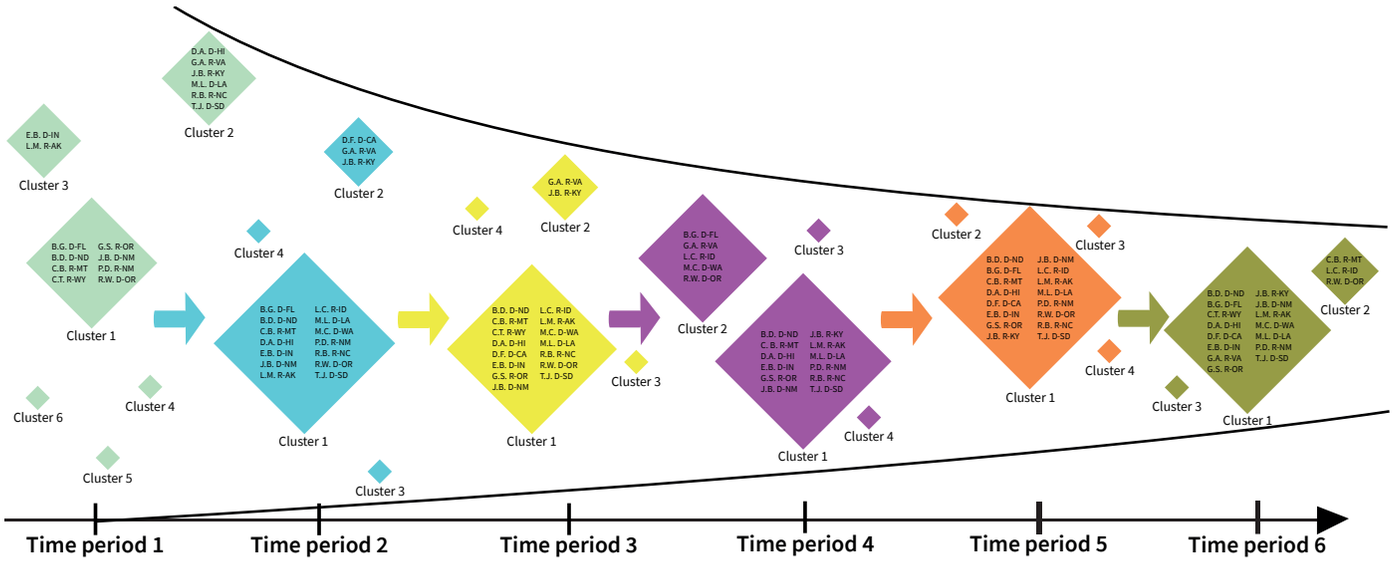

Figure 2: Dynamic clustering of legislative rhetoric in the full term data set. The CH scores are 10.65, 5.34, 5.59, 1.21, 1.29 and 0.84 for time periods 1, 2, 3, 4, 5 and 6, respectively. While the CH scores do not always decrease from one time period to the next, the overall pattern is similar to Figure 1: later periods tend to be associated with fewer clusters.

classified documents) is 0.92, which indicates an accurate classifier. We also evaluated the intercoder reliability, which is the degree of agreement between two or more coders when applying the same coding scheme, using a metric known as Krippendorff's alpha, and this resulted in a score of 0.91, which suggests a high intercoder agreement and a reliable coding scheme.

With these checks complete, we then had the algorithm analyse and classify each statement from the full data set into one of our four categories, and then, for each senator, a score was assigned, between 0 and 1, based on the proportion of their statements that were classified as "pro-lobby". Data was then reindexed so that all rhetoric began at month 1 in office following a senator's election, since our interest was in looking at how rhetoric changes in the years after election.

The data set was also split into two: the full membership data included 31 senators over 4 years (or 48 months), while the full term data included a smaller number of senators (19) over a longer time period (6 years, or 72 months – a full senate term). Both data sets were comprised of scalar-valued rhetoric scores of individual senators at time *t*.

Scores and similarities

Armed with the rhetoric scores of individual senators at different points in time, the next stage of our research involved clustering

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senators according to their rhetoric, as well as the changes to their rhetoric, over time.

The process of political group formation is intrinsically dynamic, and the number and shape of the clusters were unknown beforehand, since they could be based on partisanship, geography, constituency or other unknown subjective factors. To address these challenges, we brought in a methodology from environmental statistics, a trend-based clustering algorithm for spatiotemporal data called TRUST, which was proposed by Ciampi *et al*.[4] and Appice *et al*.[5] In environmental sciences, we may use TRUST to assess whether different locations in, say, the Chesapeake Bay share similar types of water quality trends during winter and summer seasons. Here, we apply TRUST by viewing each senator as a "location" and we cluster them in terms of the similarity of their rhetoric at different points in time. In our time series, of course, there is no spatial information, so senators are grouped as long as they share similar temporal trajectories in their rhetoric.

Figures 1 and 2 depict our findings for the full membership and full term data set, respectively. The diamonds represent the clusters, sized relative to the number of senators within. The initials of the senators, and their party and state, are shown for the larger clusters. The smaller clusters are individual senators whose speech is different from that of the rest of their colleagues; their names have been omitted to improve the clarity of the figures.

The composition of the clusters in Figure 1 reveals not only that the number of clusters diminishes over time, but also that membership becomes more concentrated in fewer clusters. Overall, the senators become more alike in their political speech.

We find a high number of clusters in the first year in office (time period 1, Figure 1) with a small number of senators in each cluster. This trend is sustained throughout the second year in office (time period 2, Figure 1), when we still observe a relatively high number of groupings, but the total number diminishes – the senators begin to form bigger clusters. A notable change occurs after the second year: the number of clusters reduces markedly, and one big, dominant cluster is formed in this period. Political rhetoric becomes more alike and both Republicans and Democrats start speaking in similar ways. This type of behaviour is associated with the process of institutionalisation; it occurs in various bureaucracies, where an outsider becomes more like those already in the institution. The trend peaks in the fourth year (time period 4, Figure 1), when the largest cluster becomes even bigger and almost all senators are included. At this point, the rhetoric towards the energy sector is very similar across parties and geography.

The clusters in Figure 1 are not based on simple party lines but show more complex dynamics. This is particularly evident in the behaviour of newer members of the committee, such as Maria Cantwell (Democrat, Washington), who joined in 2001 and falls into clusters 7, 6, 3 and 1 in time periods 1–4. Similarly, there is Jon Tester (Democrat, Montana), who joined in 2007 and sits in clusters 12, 10, 2 and 1; and Bob Corker (Republican, Tennessee), who also joined in 2007 and falls into clusters 15, 11, 1 and 1. These senators were not clustering with anyone else in the first couple of years after their elections, but their speech slowly converges with the rest of their colleagues and, by their fourth year, they are all members of the biggest cluster (cluster 1).

Figure 2 shows the clustering results for the full term data set. It includes more temporal points, but fewer senators per time period. Analysing the full term data enables us to study whether the dynamics exhibited in the full membership data are also evident here, despite the variation in the number of senators. In particular, we are interested to see whether clusters change in time periods 5 and 6 – the last two years before senators stand for re-election.

Although the numbers of clusters that the algorithm captures are different between the data sets, the dynamics are similar. The number of groups decreases over time in both data sets, although we do not observe the same sharp drop in numbers in the full term data set as we do in the full membership data set. Still, we see that, 2 years after election, most senators belong to one or two large clusters, and this is sustained until the end of their term.

Like Figure 1, the clustering in Figure 2 depicts complex dynamics not driven by partisanship. Both Republicans and Democrats follow similar strategies, and the dynamics of their rhetoric are very similar across parties and geography: in time period 1, there are a number of groupings and several individual nodes, but in time period 6, almost all senators belong to a single large cluster, which is not based on party affiliation.

Outside or inside?

Analysis of both data sets delivers similar conclusions: in the first couple of years after an election, most senators are distinct from their colleagues in terms of their political speech, but over time they become more similar.

These findings relate specifically to one Senate committee with a particular set of interests. We may or may not see similar results in other committees, or when analysing rhetoric relating to other topics, such as health care, military spending, or foreign aid.

But what we see from our analysis is that at some point within their term of office, "outsiders" can – and do – become "insiders". Though, judging by the tone and dynamics of the 2020 presidential election campaign, Donald Trump may be one of the exceptions. ■

Acknowledgement

We appreciate the assistance of Dr Ignacio Segovia Dominguez with the preparation of graphics for this article.

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