Ideal-Point Estimation Using Twitter Retweets

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Abstract

In this paper I demonstrate a method for ideological ideal-point estimation using Twitter retweets. First, I determine a relationship between US Senators and every Twitter user who has retweeted at least one of their tweets in the past seven days based on the frequency of these retweets. This data is used to determine the relationship between every pair of Senators, which is mapped on a two-dimensional space. The first dimension of my score correlates strongly with the first dimension of NOMINATE scores for the same Senators, indicating that my score can be applicable as a measure of ideology. Due to the potential differences between the ideology that my score may be measuring and the ideology that NOMINATE scores likely measure, my score may be more applicable for campaign-related research. My measure can be further expanded to include a much greater range of politicians, as well as other politically involved individuals. This would likely improve the quality of my measure, as well as enable quantitative research of ideology of a much broader base of individuals than currently possible.

Introduction

The subfield of quantifying ideology is a relatively new and underdeveloped area of political science research, yet highly important to much of the broader research in the field. The process generally involves using some source of data to essentially assign coordinates to politicians' location on an ideological spectrum. There are two widely used scores: NOMINATE scores, and their iterations, first established by Poole and Rosenthal (1985) and based on legislative roll call voting; and CFScores, created by Bonica (2014) and based on campaign finance information. Both scores can place politicians on a one-dimensional spectrum intended to approximate the left-right/liberal-conservative spectrum, where a lower value indicates that a politician is more conservative, and a higher value indicates that a politician is more liberal. 0 represents the ideological center. In this paper, I investigate whether Twitter retweets and likes can be used to construct a spatial map of distance for political candidates to approximate ideological ideal points, and if an 'ideology score' constructed using Twitter data correlates strongly with the existing, proven NOMINATE measure of ideology.

NOMINATE scores, and the derivative techniques such as DW-NOMINATE, have long been the established measure of ideology in political science research. However, because they rely on roll call data (i.e., legislative voting), they are limited to measuring incumbent politicians in legislative bodies. CFscores were developed, using campaign contribution data, to avoid these limitations. Barber (2022) called into question whether CFscores even effectively measure ideology, or instead measure some similar but distinct concept. Regardless, both of these ‘ideology’ scores have been used to investigate a wide range of issues, ranging from the motivations behind federal judge selection (Binder and Maltzman 2004), to racial stereotyping in elections (Visalvanich 2017), to how extremism affects candidate electability (Hall and Thompson 2018).

A successful social media-based ideology score, using the same general spatial techniques, would enable even more broad analysis of ideology. It could be used to estimate the ideology of local politicians with few donors, non-elected political figures, and political organizations. It could also be used to compare ideology on a multi-national scale, as Barberá (2015) does with a Twitter follower network model. In the campaign environment, it could be used to quantitatively judge the opposition and even political environment of the race (perhaps looking at shifts in ideology among the whole ballot compared to past races). This paper was itself motivated by a wish to investigate how the ideology of local candidates compares with the ideology of national candidates during the same election cycle.

Drawing from the methodology of Bonica (2014) and Bond and Messing (2015), I construct a spatial distance map of politicians’ Twitter accounts to estimate each politician’s ideal point. This is an ‘ideological plane,’ where each politician’s true ideology, known as their ideal point, is a point on the plane. My score attempts to estimate the location of these ideal points. I conduct my analysis on the campaign Twitter accounts of each member of the US Senate. I construct a network of users who have interacted with the most recent tweets from each politician and assign them distances to each politician based on their interactions with the politician’s account. I then use the quantity and magnitude of the distances of the shared users between two politicians to find the distance between the two politicians. Based on these distances, I map the politicians in a common space, which, as Barberá (2015) finds, may be an approximation of ideological distribution. Instead of using a direct reference for ideology, such as roll call voting, this method attempts to group politicians with similar ideology closer together using a different reference for their relationship, which is, in this paper, Twitter interactions. I then compare this distribution with NOMINATE to test whether my model of ideology may be valid. I find a very strong correlation of 0.919 between my score and NOMINATE scores for US Senators, indicating that my score is effective as a measure of ideology.

Literature Review

Spatial Theory

The predominant theory used to construct ideology scores is spatial theory. Every politician is placed in an ideological space at a location known as their ideal point, and decisions are presented as a set of points in that space (Poole 2005). For example, take a moderate Senator and the one-dimensional ideological space of the liberal-conservative spectrum. The options to vote for or against a conservative spending bill would be represented as points on the right and left sides of the spectrum, respectively. The Senator's ideal point would be located near the middle of this space, and the probability of their vote for either option would be represented by their distance from each option's point. The goal of ideology scores is to approximate the locations of politicians' (and other actors') ideal points.

The book *An Economic Theory of Democracy* (Downs 1957) was the first work to apply the concept of spatial theory to political ideology. Downs theorized that voters were distributed over an ideological space, although the mathematical techniques had not been developed to test this theory (Poole 2005). It was years until this was comprehensively tested regarding voter choice (Cahoon, Hinich, and Ordeshook 1978).

NOMINATE & DW-NOMINATE

Poole and Rosenthal (1985) developed the first widely successful model of ideological mapping using spatial theory, based on Congressional roll calls. Using roll call data, they were able to estimate the locations of the yea/nay outcomes along a single dimension, and then place the legislators along the space. After a number of updates (Poole and Rosenthal 1991; 1997), McCarty, Poole, and Rosenthal (1997) devised the DW-NOMINATE score, the current standard of roll-call ideological analysis. DW-NOMINATE makes minor tweaks to the methodology of the NOMINATE procedure and slightly improves the quality of the measure, but NOMINATE and DW-NOMINATE (and the earlier improvements D-NOMINATE and W-NOMINATE) are both commonly used today for essentially the same purpose.

While several scholars have critiqued NOMINATE and DW-NOMINATE as valid measures of ideology (Lee 2016; Bateman and Lapinski 2016; Caughey and Schickler 2016), these criticisms mostly center around specific applications of DW-NOMINATE scores, especially to historical research, as DW-NOMINATE scores are not comparable over time. However, as McCarty (2016) explains, the variations between versions of NOMINATE scores allow for different use cases, and McCarty is able to conduct historical comparisons using static W-NOMINATE scores.

There are significant limitations to NOMINATE scores and their derivatives. They are generally limited to a single legislative body, and although Shor and McCarty (2011) were able to develop a method to compare roll call voting across American state legislatures, such common-space comparisons are difficult or impossible between completely different political institutions or nations. Additionally, only legislators can be measured, as the metric relies on legislative roll call data.

CFscores

Bonica (2014) attempted to circumvent these limitations by constructing a spatial map of ideology through a completely different data source: campaign finance data. He constructs a map of donors and recipients that places both groups in a common space and enables the estimation of ideal points for not only legislators, but any political actor who receives or makes political contributions, such as presidents, governors, other elected state officials, interest groups, and individual voters. The first method applying contribution data to construct an ideology score was PAC-NOMINATE, developed by McCarty and Poole (2006) based on the NOMINATE model. However, it was never widely adopted. Bonica takes a different approach from the NOMINATE model by structuring the decision to make a political contribution as an allocation problem.

While CFscores have been widely used in the short time since their development, a number of concerns have been raised. Barber (2022) found that recently, the correlation between CFscores and NOMINATE scores among Democratic legislators in the US Congress has completely disappeared, indicating that the two measures are not measuring the same concept. Barber does completely discount CFscores as a valid measure of *something*, but argues that, considering the widespread acceptance of NOMINATE and similar scores as measures of ideology, CFscores are not entirely valid measures of ideology.

Social Media-Based Measures of Ideology

Several attempts have been made to use alternative data sources to construct common-space maps of ideology. Social media is a particularly promising avenue for several reasons. Social media sites are already organically created maps of a kind, and feature extremely high numbers of users, giving researchers a huge set of data to determine spatial relationships from. Additionally, social media has a much lower barrier of entry than financial contributions (only donations above $250 are included in public databases of contributions), enabling such measures to capture a more diverse base of political actors.

Bond and Messing (2015) use Facebook likes to evaluate the relationship between any two pages and construct a distance matrix, a not dissimilar technique to the one used by Bonica (2014) to construct the CFscore. They found that their method produced scores strongly correlated with both DW-NOMINATE scores and self-reported ideology scores from Facebook users, although their technique has not been widely adopted. Barberá (2015) constructed a spatial model using Twitter follows and also found strong correlation with DW-NOMINATE scores.

Tausanovitch and Warshaw (2017) evaluate several different measures of ideology, including the common-space roll call comparisons developed by Shor and McCarty (2011), CFscores, and Barberá's Twitter-based score. They find that each measure evaluates a different set of factors comprising a "political orientation," and that each measure does not capture a common scale of ideology. Importantly, this does not mean that any of these measures are necessarily invalid, just that they should not be used as proxies for the vague concept of 'ideology'. It is likely that alternative scores measure slightly different variables; for example, CFscores are almost certainly representative of patterns of political contributions, which tend to correspond with ideology, but are a separate variable.

Applications

Ideology scores, especially NOMINATE, DW-NOMINATE, and CFscores, have been used in political science to investigate a wide range of research topics. Binder and Maltzman (2004) use DW-NOMINATE scores to challenge the assumption that presidents typically defer to home state senators for federal judicial nominations and argue that instead presidents consult with senators across the ideological spectrum. Visalvanich (2017) uses CFscores to control for ideology in his investigation of how Asian candidates are affected by racial stereotyping. Hall and Thompson (2018) use

CFscores more directly, to investigate how ideologically extreme candidates perform compared to moderate candidates in primary and general elections. The Hall and Thompson paper is one of many recent works investigating the increased polarization in American politics, and ideology scores are central to many of these papers.

Theory and Data

As mentioned above, my model uses spatial theory to place political actors in an either single or two-dimensional space and assign every actor in the space a score (or multiple scores for a multi-dimensional space) representing their ideal point. Dimensionality relates to the number of different variables describing a set of data. In this case, I start with many dimensions (one for every user who retweets a Senator's tweet) and attempt to reduce the data to one or two dimensions which accurately capture the ideology of the Senators. NOMINATE and its derivatives have extensively proven the validity of ideal point analysis as an estimation of legislator ideology, although it is unclear whether it is as valid as a measure of the ideology of other political actors. Regardless, the prevalence of CFscores in political science research demonstrate that ideal points have already been used to approximate the ideology of a range of political actors.

I use Twitter retweets as my primary source of data, and I initially construct my model using data from US Senators' accounts. Senators provide a large but not unmanageable sample of data to pull from and enable me to easily compare my results with the established NOMINATE score. I pull the users who have retweeted the most recent tweets, over a seven-day span, from every US Senator to evaluate the strength of the relationship between each user and the politician in question, based on how many of their most recent tweets they have retweeted. I have chosen retweets for this primarily because they are generally an expression of agreement or support, and also are easily accessible through the Twitter API, which I am using to extract the data. Retweets come with a couple of limitations. On the Twitter accounts of less popular senators, the number of retweets tends to be limited, and this would present an even more severe problem when attempting to expand my score to local politicians. Additionally, retweets do not always indicate agreement. Many journalists and similar figures use retweets to inform their audience about a tweet, without necessarily agreeing with the message. However, I do not expect this bias to significantly affect the quality of my measure, as most of the tweets which are retweeted by journalists are prominent tweets which typically attract higher numbers of retweets, reducing the impact of retweets from journalists. There is another potential source of bias when using data from Twitter interactions. Generally, Twitter users who interact with politicians are more politically aware than the average citizen (Barberá 2015). However, this may actually be a positive when attempting to measure ideology. It is reasonable to assume that more politically aware individuals are also more likely to have a more defined concept of their own ideology and are thus more likely to heavily favor interactions with politicians who closely match their ideology.

Expectations

My expectations of the performance of my model are moderate, especially considering the findings of Tausanovitch and Warshaw (2017). I hypothesize I will find a strong correlation (> 0.75) between my scores and NOMINATE scores for US Senators, as this is the set of politicians who I will initially base my model on. This correlation will, to an extent, be the result of overfitting. However, I am not worried about this as an issue, because I am focused on developing an expandable framework to produce ideology measures of a much wider range of politicians, instead of a robust model to conduct research directly. While I am limited by computational power from incorporating a large number of politicians and users into my model, my technique should be scalable to incorporate a very wide range of politicians and political actors from all levels of American government. A much larger model also has the potential of demonstrating stronger correlation with NOMINATE scores, as the larger base of Twitter users should yield more accurate results.

Methods

Generally drawing from the methodologies used by Bonica (2014) to construct CFscores and Bond and Messing (2015) to estimate ideal points using Facebook interactions, I construct a matrix of politicians and Twitter users, with politicians on the vertical axis and users on the horizontal axis. The cells contain the number of times the given user retweeted the politician's recent tweets, divided by the total number of the politician's recent tweets. The first ten rows and columns of my matrix can be seen in

Table 1. At this point, I had to remove two Senators, Ben Sasse (R-NE), and Richard Burr (R-NC), from my analysis, as they had no tweets in the time period I analyzed.

	User 1	User 2	User 3	User 4	User 5	User 6	User 7	User 8	User 9	User 10
Richard Shelby	1	0.1	0.4	0.2	0.1	0.1	0.1	0.1	0.1	0.1
Tommy Tuberville	0	0	0.0625	0	0	0.03125	0	0	0	0
Lisa Murkowski	0.5	0	0	0	0	0	0	0	0	0
Dan Sullivan	1	0	0	0	0	0	0	0	0	0
Kyrsten Sinema	0.5	0	0	0	0	0.096154	0	0	0	0
Mark Kelly	0	0	0	0	0	0.045455	0	0	0	0
John Boozman	0.512195	0	0	0	0	0	0	0	0	0
Tom Cotton	0.297297	0	0	0	0	0.297297	0	0	0	0
Dianne Feinstein	1	0	0	0	0	0	0	0	0	0.045455
Alex Padilla	0	0	0	0	0	0.038462	0	0	0	0

Table 1: *The first ten rows and columns of the matrix of politicians and Twitter users. The values are the number of times that the given user retweeted the given politician divided by the total number of the politician's recent tweets.*

To reduce the dimensionality of this matrix and extract a single-dimensional score, I use correspondence analysis (CA). However, this matrix is quite large, with 50 Senators by 297,609 users, and containing 14,880,450 values in total. Because of this, it would be extremely computationally difficult to perform CA on this matrix directly. Thus, I convert this matrix to an affiliation matrix between the Senators. By considering each value in my original matrix as a measure of the strength of the relationship between each given Senator and user, I take each pair of Senators and find every user which has retweeted tweets from both. For each user, I take the average of the relationships between the user and the two Senators. I then add up the averages for all of the users which have retweeted both Senators, indicating some magnitude of the relationship between each pair of Senators, which is contained in the affiliation matrix. The diagonal entries of the affiliation matrix contain the total number of retweets each

Senator received in the time period analyzed, divided by their number of retweets during that time period. By dividing any off-diagonal entry by a corresponding diagonal entry in the same column, I can calculate the ratio of retweets for any given Senator related to their relationship with another Senator. The first ten rows of the affiliation matrix can be seen in Table 2.

	Shelby	Tuberville	Murkowski	Sullivan	Sinema	Kelly	Boozman	Cotton	Feinstein	Padilla
Richard Shelby	**6.333333**									
Tommy Tuberville	0.296875	**100.3158**								
Lisa Murkowski	0.75	0.091346	**146.3846**							
Dan Sullivan	1	1.408482	1.864011	**12.41667**						
Kyrsten Sinema	0.848077	0.455529	3.413462	0.75	**32.69231**					
Mark Kelly	0.072727	0.269886	26.64685	0.279221	17.80594	**5875.75**				
John Boozman	0.756098	0.530488	0.588884	1.33101	0.506098	0.08204	**5.846154**			
Tom Cotton	0.960811	40.60684	1.738825	9.067568	3.428534	3.627457	2.98385	**1967.083**		
Dianne Feinstein	1.072727	0	4.254371	1	2.833916	15.96591	0.756098	1.92199	**98**	
Alex Padilla	0.069231	0.060096	6.057692	0.181319	3.951923	62.47465	0	1.563669	7.948427	**111.3333**

Table 2: *The first ten rows and columns of the affiliation matrix between all of the Senators. Off-diagonal values indicate the magnitude of the relationship between any two Senators. Diagonal values indicate the average number of retweets a Senator received on their tweets.*

By performing these divisions on each entry in the matrix, I produce an agreement matrix (Table 3) containing the scaled values representing the relationship between every Senator. As opposed to the affiliation matrix, the agreement matrix is asymmetric across the diagonal because of the matrix division by the average number of retweets from each Senator. For example, the values in Senator Mark Kelly's column are much smaller than those in his row, despite them both representing his relationship with each other Senator, because his average number of retweets is very high.

	Shelby	Tuberville	Murkowski	Sullivan	Sinema	Kelly	Boozman	Cotton	Feinstein	Padilla
Richard Shelby	1	0.005919	0.010247	0.161074	0.051882	2.48E-05	0.258665	0.000977	0.021892	0.001244
Tommy Tuberville	0.09375	1	0.001248	0.22687	0.027868	9.19E-05	0.181483	0.041286	0	0.00108
Lisa Murkowski	0.236842	0.001821	1	0.300243	0.208824	0.00907	0.20146	0.001768	0.086824	0.108821
Dan Sullivan	0.315789	0.028081	0.025467	1	0.045882	9.50E-05	0.455346	0.009219	0.020408	0.003257
Kyrsten Sinema	0.267814	0.009082	0.046637	0.120805	1	0.006061	0.173139	0.003486	0.057835	0.070993
Mark Kelly	0.022967	0.005381	0.364066	0.044975	1.089305	1	0.028066	0.003688	0.325835	1.122299
John Boozman	0.238768	0.010576	0.008046	0.214391	0.030961	2.79E-05	1	0.003034	0.015431	0
Tom Cotton	0.303414	0.80958	0.023757	1.460548	0.209746	0.001235	1.020791	1	0.039224	0.02809
Dianne Feinstein	0.338756	0	0.058126	0.161074	0.173369	0.005435	0.258665	0.001954	1	0.142786
Alex Padilla	0.021862	0.001198	0.082764	0.029206	0.241765	0.021265	0	0.00159	0.162213	1

Table 3: *The first ten rows and columns of the agreement matrix between all of the Senators. This is produced by dividing each column of the affiliation matrix by the diagonal values.*

Finally, I perform a correspondence analysis on the agreement matrix to reduce the dimensionality of my data. The CA produces two matrices of results, one representing the components of the data contained in the rows of the table, known as the left-singular vectors of the original matrix, and one representing the components of the data contained in the columns of the table, known as the right-singular vectors of the original matrix. This is an oversimplification but describes the essential aspects of CA for this research. If I were to perform a CA on the original matrix of Senators and users, the left-singular vectors would represent the ideology of the Senators, and the right-singular vectors would represent the ideology of the users. However, because I use a matrix of Senators by Senators, and I scale the columns, instead of the rows, to account for different quantities of retweets, I use only the right-singular vectors as my ideology score. For practicality purposes, I retrieve the first two dimensions of the right-singular vectors, which are the two most descriptive dimensions. To compare to the first dimension of NOMINATE scores, I use only the one-dimensional estimation of the ideal points generated by my model and use Pearson's correlation coefficient to determine the correlation between the two scores.

Results and Analysis

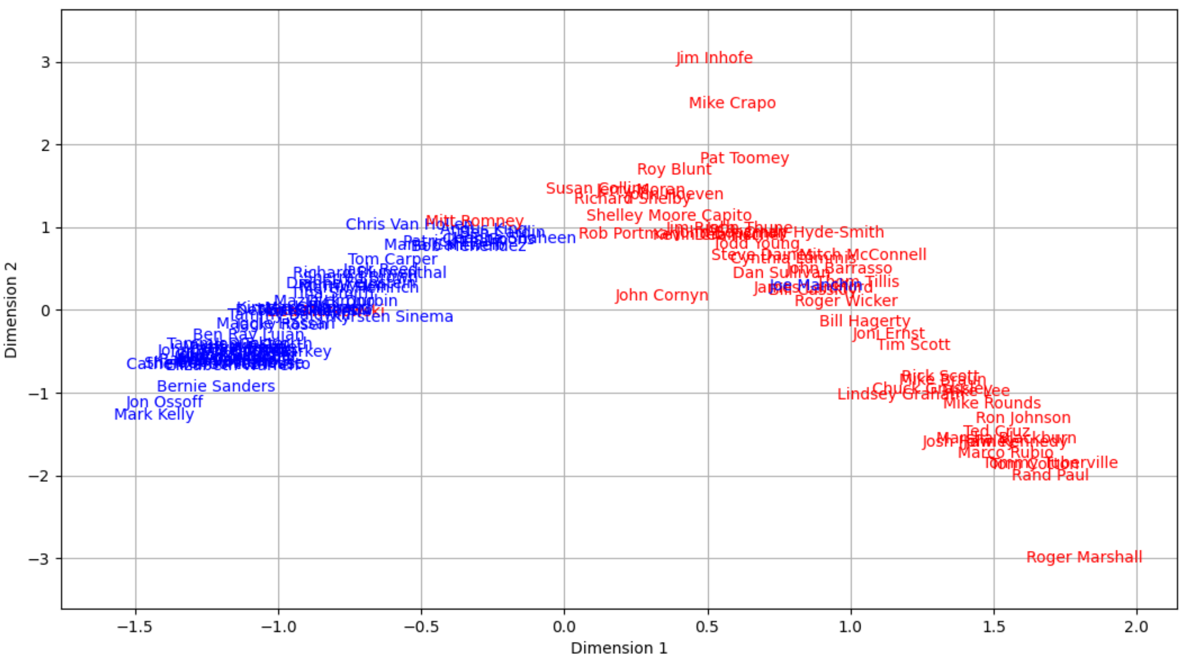

__Figure 1:__ The first two dimensions of my ideology score for each Senator.

The graph of the first two dimensions of my ideology score can be seen in Figure 1. It is evident from a glance that the first dimension is quite representative of the left-right ideological divide, and my model not only effectively divides nearly every Senator by party, but even places many of the more ideologically extreme Senators, such as Bernie Sanders (I-VT) and Rand Paul (R-KY) further to the edges of the graph. This figure also seems to indicate that the second dimension may be representative of ideological extremism regardless of which end of the extreme a politician is on but verifying this would involve further research. Figure 1 also contains a few results which highlight some potential limitations of my score, at least for this initial iteration. Joe Manchin (D-WV), Mitt Romney (R-UT), and Lisa Murkowski (R-AK) appear to be outliers in their parties according to ideology. However, there are clear explanations for this result for all three. Romney and Murkowski both had very popular tweets in support of the Respect for Marriage Act, a largely Democratic-favored bill, during the seven-day period from which I collected retweets. Because of the popularity and unusual audience for these tweets, their scores have been biased. Manchin, while a Democrat, has consistently played spoiler for significant pieces of Democratic legislation since President Biden's election, and it is likely that he is simply more popular amongst Republicans than Democrats at this time.

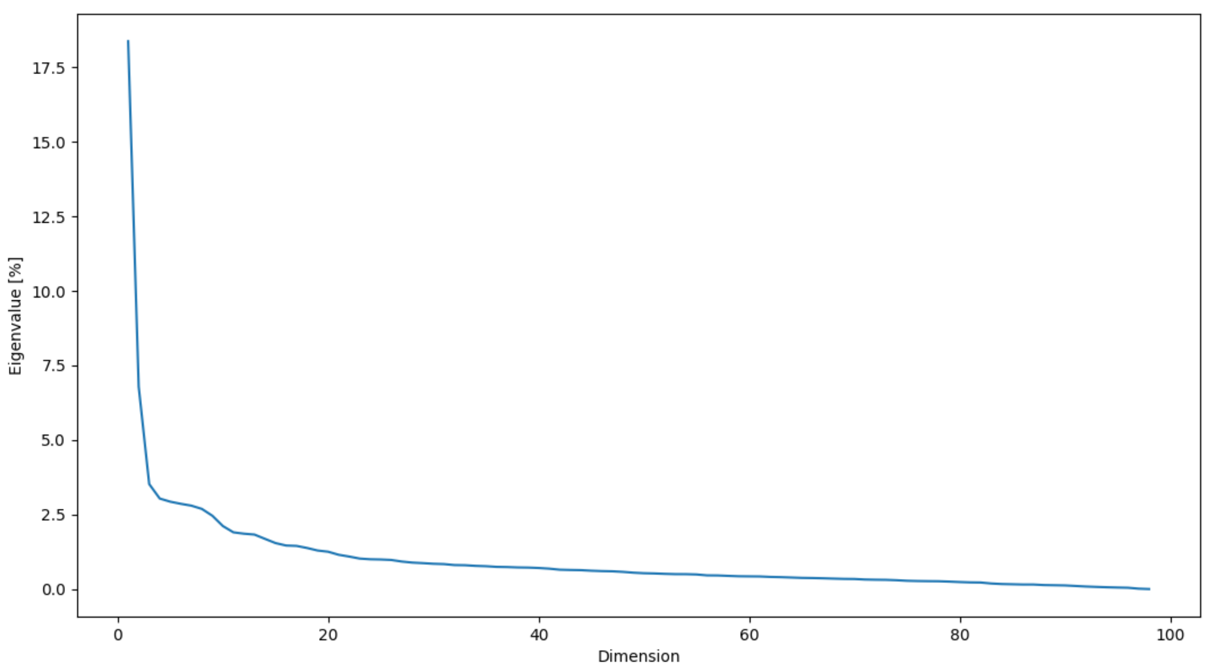

Figure 2: *The eigenvalue percentage for each dimension, indicating how much of the variation in data each dimension explains.*

Figure 2 displays the eigenvalue percentage of each dimension of my score, indicating how much each dimension captures the total variation in the data. It clearly indicates that the first few dimensions are by far the most indicative of the total variation in data. The first dimension explains 18.37% of the total variation; the second dimension, 6.79%; the third dimension, 3.52%; and the fourth dimension, 3.04%. No other dimension captures more than 3% of the total variation. While this shows that there is significantly more variation to the data than can be explained by only one or two dimensions, it also means that the first dimension alone is representative of a large amount of the total variation.

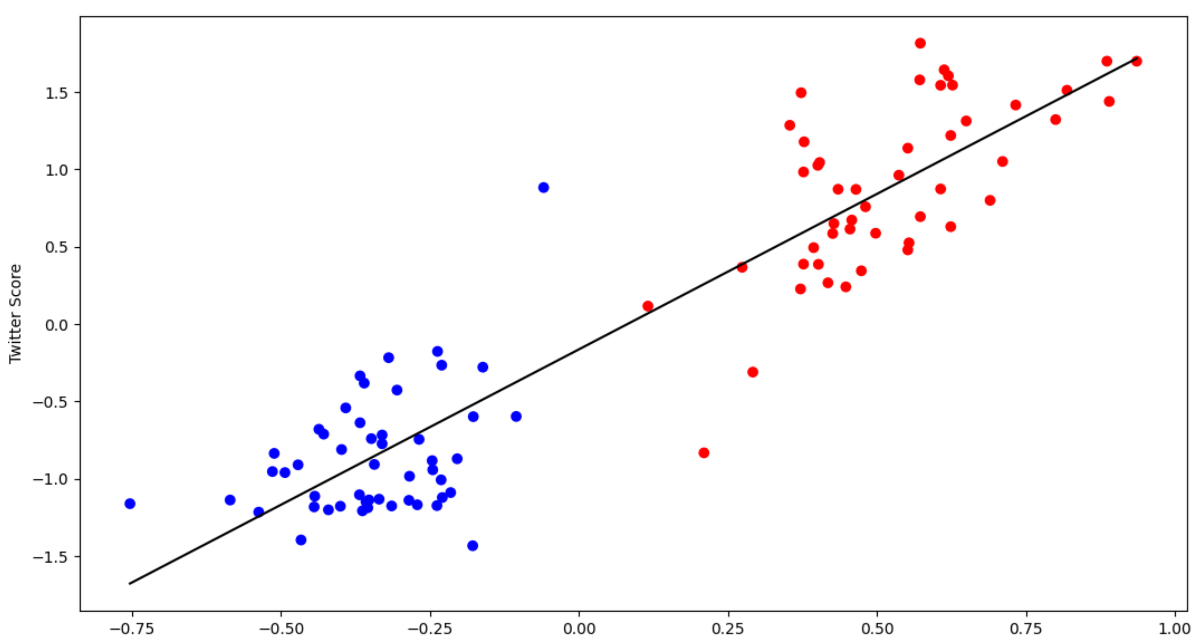

Figure 3: *Scatter plot of the relationship between my Twitter score and the standard for ideology scores, NOMINATE, for each Senator I analyzed.*

Figure 3 shows the relationship between my constructed Twitter score and NOMINATE, used as the standard (as well as its derivatives) for quantitative measures of ideology. The Pearson correlation coefficient for this relationship is 0.919, with a P-value of close to zero. This means that the relationship between the two scores is very strong and statistically significant. While it is impossible to fully determine what the Twitter score is measuring exactly, this is a major indication that the two scores are measuring close to the same thing. Considering that it is widely accepted that NOMINATE scores measure ideology, this indicates that my score can also be used as a proxy for ideology.

Discussion

Overall, my results indicate that my method of constructing a spatial map of ideology based on Twitter interactions has promise as a quantitative ideology measure. The correlation I found with NOMINATE scores is much stronger than I hypothesized. My score is not perfectly correlated with NOMINATE scores, although this does not necessarily invalidate this conclusion in any way. It may actually be important that the two scores differ, as a Twitter-based score can offer a different measure of what ideology is compared to NOMINATE.

Because NOMINATE scores are based on legislative roll-call data, they most closely capture how the ideology of politicians plays out in legislative bodies. However, there is an argument to be made that this is not their 'true' ideology: legislators may often vote strategically or based on the interests of their constituents rather than their own ideological ideal point. Additionally, legislators can mostly only vote on bills that are put in front of them, so an ideologically extreme politician may not get the chance to express their extremism when only relatively moderate bills reach the floor.

In contrast, users on Twitter occupy a much broader ideological range. It is almost an inside joke that you can find any ideology, no matter how niche, on the political spaces of Twitter. Politicians are also free to express more extreme or nuanced views on Twitter, and users make their own judgements on whether they agree with them, or if they match their own ideological ideal point. Essentially, I am measuring not the ideology that politicians outwardly express, but the ideology that people perceive they outwardly express, crowdsourcing this information into a robust measure. For campaigning and campaign-related research, this is more important to determine than how a politician will express their ideology once in office, because campaigning is based on voter perception rather than votes in Congress.

Conclusion

While ideology is a common variable used in political science research today, current methods of generating quantitative measures of ideology are still incredibly limited. NOMINATE scores are generally accepted as successful measures of ideology but are limited in the set of politicians they can evaluate, and comparisons between different political institutions are difficult. CFscores avoid some of these limitations, but recent research (Barber 2022) has called into question their validity. Social media-based scores avoid several of the concerns with CFscores, especially by including a more diverse and inclusive dataset.

This paper is intended as a proof-of-concept rather than a full-fledged ideology measure ready to be used for research. There are several ways to expand on this work and improve the model. Firstly, greatly expanding the amount of data integrated into my model, especially by expanding the base of politicians included, should further improve the accuracy of my scores, reduce outliers caused by one or a few tweets (such as the results for Senators Romney and Murkowski), and improve the applicability of my measure. One of the most promising uses for my technique is to accurately quantify the ideology of local and other politicians not in legislative bodies, as well as other politically involved individuals who may not even be politicians. Expanding my score to these individuals and determining some way of validating my score for them, would be an incredibly important development for political science research, especially for campaigns. Another potential avenue to improve my score would be to integrate Twitter likes into my estimates of the relationship between politicians and users. These expansions would require considerably more computing power and research time than this current work, and alternate techniques may be necessary to reduce the computational demands of my methods.

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Appendix

Item A: The first two dimensions of my Twitter score for every Senator I analyzed. The first dimension captures 18.37% of the total variation in ideology, and the second dimension captures 6.79%.

Senator	Dimension 1	Dimension 2
Richard Shelby	0.240448	1.33987
Tommy Tuberville	1.699521	-1.85951
Lisa Murkowski	-0.83267	-0.01841
Dan Sullivan	0.758355	0.438387
Kyrsten Sinema	-0.59725	-0.08699
Mark Kelly	-1.43336	-1.27788
John Boozman	0.58556	0.926953
Tom Cotton	1.643875	-1.86825
Dianne Feinstein	-0.74561	0.31608
Alex Padilla	-1.20115	-0.62041
Michael Bennet	-1.12174	-0.46082
John Hickenlooper	-1.17384	-0.49605
Richard Blumenthal	-0.68031	0.437203
Chris Murphy	-1.16857	-0.58015
Tom Carper	-0.59854	0.601653
Chris Coons	-0.26597	0.846746
Marco Rubio	1.543984	-1.72956
Rick Scott	1.313182	-0.81333
Jon Ossoff	-1.39603	-1.11616
Raphael Warnock	-1.17782	-0.60853
Brian Schatz	-1.18219	-0.62675
Mazie Hirono	-0.83612	0.100955
Mike Crapo	0.587256	2.491634
Jim Risch	0.479536	0.983173
Dick Durbin	-0.74094	0.099167
Tammy Duckworth	-1.13222	-0.41369
Todd Young	0.672575	0.789446
Mike Braun	1.322108	-0.85572
Chuck Grassley	1.285371	-0.95411
Joni Ernst	1.137392	-0.2902
Jerry Moran	0.266796	1.448857
Roger Marshall	1.816003	-3.00399
Mitch McConnell	1.044564	0.652534

Rand Paul	1.699706	-2.01007
Bill Cassidy	0.870834	0.232624
John Kennedy	1.578869	-1.59529
Susan Collins	0.116034	1.460969
Angus King	-0.27878	0.972799
Ben Cardin	-0.21729	0.929268
Chris Van Hollen	-0.54212	1.021389
Elizabeth Warren	-1.1614	-0.67132
Ed Markey	-0.95373	-0.51048
Debbie Stabenow	-0.90753	-0.00631
Gary Peters	-0.8832	-0.01026
Amy Klobuchar	-1.1396	-0.56288
Tina Smith	-0.81131	0.198243
Roger Wicker	0.98327	0.098661
Cindy Hyde-Smith	0.871763	0.925251
Roy Blunt	0.386325	1.691447
Josh Hawley	1.416286	-1.59991
Jon Tester	-1.08953	-0.41182
Steve Daines	0.694489	0.662538
Deb Fischer	0.614227	0.906563
Catherine Cortez Masto	-1.2075	-0.66615
Jacky Rosen	-0.98397	-0.18262
Jeanne Shaheen	-0.17677	0.867008
Maggie Hassan	-1.00736	-0.16641
Bob Menendez	-0.3351	0.76687
Cory Booker	-1.13785	-0.50012
Martin Heinrich	-0.71735	0.269264
Ben Ray Lujan	-1.10362	-0.30555
Chuck Schumer	-1.14883	-0.54981
Kirsten Gillibrand	-0.90996	0.023392
Thom Tillis	1.026257	0.327684
John Hoeven	0.387603	1.396389
Kevin Cramer	0.494148	0.904913
Sherrod Brown	-0.71158	0.385476
Rob Portman	0.226892	0.913289
Jim Inhofe	0.525331	3.030136
James Lankford	0.873359	0.262131
Ron Wyden	-0.77397	0.290292
Jeff Merkley	-1.11299	-0.4744
Bob Casey Jr.	-1.17604	-0.60509

Pat Toomey	0.629623	1.824633
Jack Reed	-0.63816	0.480384
Sheldon Whitehouse	-1.18781	-0.64221
Lindsey Graham	1.178364	-1.02826
Tim Scott	1.219199	-0.42828
John Thune	0.649733	0.981496
Mike Rounds	1.495628	-1.13204
Marsha Blackburn	1.544969	-1.55656
Bill Hagerty	1.05119	-0.14986
John Cornyn	0.344345	0.174975
Ted Cruz	1.511686	-1.47001
Mike Lee	1.439554	-0.99012
Mitt Romney	-0.3106	1.071153
Patrick Leahy	-0.38176	0.826889
Bernie Sanders	-1.21597	-0.92605
Mark Warner	-0.8709	0.016058
Tim Kaine	-0.94246	-0.01504
Patty Murray	-1.13728	-0.4686
Maria Cantwell	-0.42688	0.774645
Joe Manchin	0.882793	0.296023
Shelley Moore Capito	0.367183	1.137346
Ron Johnson	1.605258	-1.31832
Tammy Baldwin	-0.96016	-0.06578
John Barrasso	0.962397	0.492899
Cynthia Lummis	0.799868	0.614368