Measuring State Preferences: Using Networks, Combing Indices☆

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Abstract

We do things.

☆Thanks to people.

2. Introduction

2.1. Why we care about preferences

Compared to other concepts in the study of international conflict and cooperation, state preferences have been understudied. Perhaps this is a consequence of black box theories of international relations, where it is assumed that all state preferences can be reduced to an automatic desire for more power. Alternatively, it may be because it is more difficult to measure something like preferences, as compared to more tangible material or institutional factors.

Yet this relative dearth of attention should not be assumed to be caused by the relative unimportance of preferences in the study of international processes. A number of formal theories of international relations require measures of preferences to be tested: the expected utility theory proffered by (**?**) has similarity of preferences as an important input, and attempts to expand studies of crisis bargaining to include coalitional dynamics (**?**), mediation (**?**), or the possibility of additional disputants (**?**) require a measure of state preferences in order to predict whether war will be the result of bargaining failure. As **?** has pointed out, preferences have been used in empirical studies predicting bilateral trade, foreign aid, stability of international institutions and the incidence of conflict (**?????**).

Preferences similarly pose the risk of omitted variable bias in a number of issues of paramount concern: without a good measure of preferences, it would be difficult to entangle whether democracies avoid war with other democracies because of the intrinsic nature of democracy, or simply because they happen to have common ends; similarly attempting to assess the impact of crisis behavior on a state's reputation requires us to determine how acceptable an outcome was to the state, as (**?**) does in his study of interdependence and resolve. Finally, measures of preferences can yield insights as an independent variable in their own right: they could be used to see if Edward Snowden's revelations about the United States spying caused states to move their preference away from the US's, to see how the United States's preferences towards states in the Middle East changed after 9/11, or to see the impact of Russia's annexation of Crimea on their relations with their satellite states and Western Europe.

2.2. *Sources of Preference Measures: Alliance Portfolios and UN Voting*

Given that we cannot directly observe state preferences, scholars have attempted to ascertain it using two main behavioral indicators: who states choose to ally with, and how states vote at the United Nations. The idea behind alliance portfolio measures is that we can infer a state's foreign policy by looking at the states they choose to align with. In the extreme case, if two states have all of the same allies, it is likely that their foreign policy goals are quite similar. Conversely, if all allies of one state are not allied to another, and vice versa, our best guess is that these states would have different aims and desires in foreign policy. **?** encapsulate the logic when they note that "alliance commitments reflect a nation's position on major international issues." Measures of alliance behavior also suffer from the relatively glacial movement and sparsity in these relationships. Formal alliances are relatively constant over time, whereas in many cases state preferences will be more fluid, and therefore these scores will be at best a lagging indicator of preferences. Furthermore, as **?** points out, the fact that links are so rare creates artificial similarity of alliance portfolios.

We also have a relatively large corpus of somewhat behavioral information in UN Voting Records. The cost of voting in the UN is low, and so, scholars have argued that measures of affinity based on UN voting are relatively representative of the underlying distribution of preferences (**?**). This is especially fortuitous because the methodology of inferring preferences from voting in a legislature is relatively advanced. A few issues with these measures are that the potential benefit of winning UN votes is low, and so states might have incentives to vote against their preference as they are not costly signals, and the distribution of UN voting is weird and prone to large supermajorities of the type rarely seen in “ordinary" legislatures.

2.3. *Current measures of preferences: S-Scores*

The initial measures used to measure preference similarity based on alliance portfolios was Kendall’s τ_B **?**. This measure is:

$$\tau_B = \frac{n_c - n_d}{\sqrt{(n_0 - n_1)(n_0 - n_2)}} \tag{1}$$

where n_c is the number of pairs where both actor i and j have the same rank ordering (for example both the UK and the US are more closely allied to Israel than to Iran), n_d is the number of pairs where they have discordant rankings (the US is more closely allied to Saudi Arabia than to Russia, Syria is more closely allied to Russia than to Saudi Arabia). The denominator attempts to adjust the total number of pairs with the number of ties: n_0 is the total number of pairs ($n(n-1)/2$), n_1, n_2 are measures for ties in both i and j’s rankings respectively.

? convincingly pointed to flaws in this measure, notably its focus on rank-ordering as applied to a context where we instead care mostly about the presence or absence of an alliance. In addition, if we add additional strategically irrelevant states, we will create artificially high τ_B statistics. Thus, Signorino and Ritter introduce the S score, which has since been the most widely used alliance similarity measure.[1]

[1](**?**) also find a stronger relationship between theoretical predictions and results when using S-scores than when using τ_B

The equation for the S score is:

$$S(P^i, P^j, W, L) = 1 - 2w_k \frac{d(P^i, P^j, W, L)}{d^{\text{max}}(W, L)} \tag{2}$$

Where:

$$d(P^i, P^j, W, L) = \sum_{k=1}^{N} \frac{w_k}{\Delta_k^{\text{max}}} |p_k^i - p_k^j| \tag{3}$$

Where w_k is the k'th element of a weight matrix, $d^{\text{max}}(W, L)$ is the maximal distance on a given dimension, and Δ is a normalizing constant. For the weight matrix, generally analysis has used S scores calculated with a weight matrix of ones–giving each potential ally equal weight–though the other plausible choice would be to weight states by import, for example using their share of world military capability, as calculated by **?**.

One important distinction for these scores is that they are purely dyadic. One can look at the S-score between two states, but one cannot look at a state's preferences in comparison to a larger cluster, or note the movement a states preferences made over time. In monadic analysis, these score measures are not even available, and once we are dealing with situations involving more than two states, the number of S-scores necessary to fully characterize the preferences balloons quickly (it is the number of actors choose two). **?** attempted to apply a similar S-score methodology to UN voting data and created the "Affinity of Nations" index.

One advantage, however, of using UN General Assembly Voting, is that it allows you to take advantage of methodological advances in the study of legislatures. **?** do so by using an Item Response Theory model on UNGA voting. This model seeks to place states on a unidimensional latent preference space using their voting behavior. The assumption of this model is that states' votes on a resolution are a function of states' ideal points, characteristics of the vote, and random error. In particular, for each bill v, a states vote will be based on the latent variable Z_{itv}

$$Z_{itv} = \beta_{iv}\theta_{it} + \epsilon_{iv} \tag{4}$$

such that the state will vote yes if $Z_{itv} < \gamma_{1v}$, no if $Z_{itv} > \gamma_{2v}$ and otherwise abstain. Here, θ_{it} is state i's ideal point at time t, and β_{iv} is the discrimination parameter of a particular bill v. When β_v is positive, states with high ideal points will be more likely to vote no. When it is negative, they will be more likely to vote yes.

The authors specifically fix the parameters γ_{1v} and γ_{2v} such that the same bill will have the same value in different years, and they standardize and normalize θ. They also use θ_{it-1} as a prior on θit. With these constraints, they solve for the ideal points and outpoints using a Metropolis Hastings MCMC.

The issues here are that the voting behavior, especially in the EU general assembly, is not well behaved in the way that voting in the US Congress is. We actually can get some sense of it by the existence of multiple identical resolutions: UN resolutions have no legal force, and so most votes are symbolic. Thus UN voting is rife with nearly unanimous voting and other super-majorities, which means that the requirements to distinguish between state preferences are more onerous. Another issue here, not necessarily with use of voting in general, but with this application, is the limitation to one dimension: it could be that two states which have very similar preferences on issues of trade – say the United States and Saudi Arabia – might differ mightily on questions related to the Middle East, and in particular Israel.[2] However, the dearth of contentious UN votes makes it difficult to add additional dimensions.

[2] You can see issues like this on legislative positions in the United States: during the post WW2 era, two democrats who might agree on the need to expand the social safety net might be diametrically opposed on issues of civil rights.

2.4. Synthesizing Measures of State Preference

We propose that preferences and ideal points can be better measured by combining multiple proxies, and accounting for network interdependencies. Obviously, the idea of using multiple metrics to get a better handle on preferences is not new, in fact Signorino and Ritter suggested it in introducing S scores, which were designed to allow for aggregation of similarity on multiple dimensions (such as alliances and UN voting). What we propose, is to combine the dyadic measures of state similarity created using S-scores for alliances, and using voting models for UN data, in a manner that is both principled, and allows us to account for interdependencies. In particular, we use these two measures of state preference in a network model, in order to ascertain the state positions that best explain not only states dyadic similarity and dissimilarity on both measures, but also why states form the clusters they form. Our hope, is that by combining different measures of state preferences, and better accounting for spatial dependencies, we are able to generate a measure for preference that maintains the insights of both UN voting scores and S-scores, but which can also yield some new insights, in particular, when it comes to predicting and explaining interstate conflict.

3. Methodology

3.1. AME, Why Network stuff matters

We want a model that takes a set of actions between countries, and infers each countries position in a latent preference space, such that those countries close to each other are likely to have similar preferences and therefore have similar alliances and UN voting records. We would like this methodology to be able to, in a principled way combine different sources of data, for example imputing ideal points based on both alliance behavior and behavior at the UN. Finally, and importantly, this method should be able to account for interdependencies: similarity in preferences should be transitive

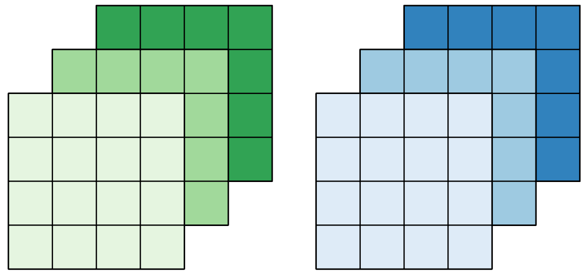

Figure 1: Tensor representation of longitudinal dyadic, representational measures. The green and blue colors represent different relational measures and darker shading indicates later time periods. Specifically, we show a tensor with dimensions of $4 \times 4 \times 2 \times 3$, where 4 represents the number of actors, 2 the number of relational measures, and 3 the number of time points.

(if the US has similar preferences to the UK, and the UK to France, the US's preferences should be relatively close to France's) and should allow for clusters of states with similar preferences.

The Additive and Multiplicative Effects model (AME) model is a relatively new technique that is a generalization of the Generalized Bilinear Mixed-Effects model from **?**. The model is an extension of the Social Relations Model:

$$f(Y_{i,j}) = \beta^{'}\mathbf{x_{i,j}} + \alpha_i + b_j + \epsilon_{i,j} \quad (5)$$

where $f(.)$ is a general link function corresponding to the distribution of Y, $\beta^{'}\mathbf{x_{i,j}}$ is the standard regression term for dyadic and nodal fixed effects, α_i, b_j are sender and receiver random effects, and $\epsilon_{i,j}$ is an IID error term. The AME model further decomposes the error term as follows. If we assume the matrix representation of deviation from the linear predictors and random effects is $\mathbf{Z}$, then $\mathbf{Z} = \mathbf{M} + \mathbf{E}$ such that the matrix $\mathbf{E}$ represents noise, and $\mathbf{M}$ is systematic effects. By matrix theory, we can decompose $\mathbf{M} = \mathbf{UDV}^{'}$ such that $\mathbf{U}$ and $\mathbf{V}$ are are n x n matrices with othonormal columns, and $\mathbf{D}$ is an n x n diagonal matrix. This is called the singular value decomposition of $\mathbf{M}$.

We then write the AME model for a given value $Y_{i,j} \in \{0, 1\}$:

$$\text{logit}(P(Y_{i,j} == 1|x_{i,j}) = \beta' \mathbf{x_{i,j}} + \alpha_i + b_j + \mathbf{u_i D v_j'} + \epsilon_{i,j} \tag{6}$$

In estimating preference models, we abstain from using fixed effects save an intercept.

An important innovation with the AME, as compared to previous network estimates is the ability to handle replicated datasets – here we use the replicated dataset to incorporate multiple measures of similarity into a single ideal point estimation. The AME with dyadic data treats each different slice of data as independent, save for those dependencies captured by the nodal and multiplicative random effects, as well as those controlled for by fixed effects. The final estimating equation we use is:

$$\text{logit}(P(Y_{i,j_j} == 1) = \mu + \alpha_i + b_j + \mathbf{u_i D v_j'} + \epsilon_{i,j,t} \tag{7}$$

What is particularly useful here is the eponymous multiplicative effect $\mathbf{u_i D v_j'}$. This effect not only helps to account for homophily and stochastic equivalence, it also places each state in a latent space. What is key to understand about this latent space is that it is non-euclidian. Rather than have states behave similar to the states which are close to them, this latent space is a two dimensional representation of a hypersphere, and thus states are apt to behave similarly to the states that are placed in the same direction on said sphere. Thus, if two states vectors (from the center of the space) are in the same direction, they are apt to send and receive both alliances and co-voting to similar targets. The way we measure this similarity in dimension is by looking at the absolute distance of the angles created by each states position and the center of the latent space.

3.2. Data Sources, Modeling choices

We use the AME model on the two aforementioned measures of state amity to generate a combined measure of state preference similarity which accounts for network effects. We use the distance between states' ideal points (as calculated by **?** using UN data) and S-score for two states alliance portfolios. However, to facilitate comparison between the metrics, we first transform the S-score into a measure of distance between alliance portfolios.[3] We then standardize and normalize these two measures. This gives us an N by N by Y by 2 array, where the first two dimensions represent countries, the third dimension is the year, and the fourth is the particular measure of similarity. So the item at index (1,2,1,1) would be the transformed value of the S-score for countries XXX and YYY at the first year of our data (YYYY), similarly (1,2,1,2) would be the UN ideal point distance.

Another important question is the amount of temporal aggregation used. In our baseline model, we treat each year as separate and gain a unique observation of each states ideal point in each year. However, this raises a real risk of temporal inconsistency in the values. An alternative approach would be to have a rolling average for the measures of similarity over a number of years. This would allow us to infer a country's relative position not just by their behavior in a given year, but also their behavior in the past few years. The risk if we use too much temporal aggregation is that we are including data which is no longer relevant to a country's relative preferences. For instance, Turkey and Russia's relationship looks a lot more positive when we look at 2013 and 2014 then when we look at 2015. To that end, in addition to our baseline model where years are seen as independent, we also evaluate models where ...

With this data, we run an AME model with a Gaussian link, and in particular we use

[3] D = 1 - S

the uDv term to estimate each states position in a two-dimensional latent space. We then evaluate whether their is additional utility gained from using this latent position, as compared to the component measures of similarity of alliance portfolio and UN ideal point distance.

4. Constructing Latent Angle Measure

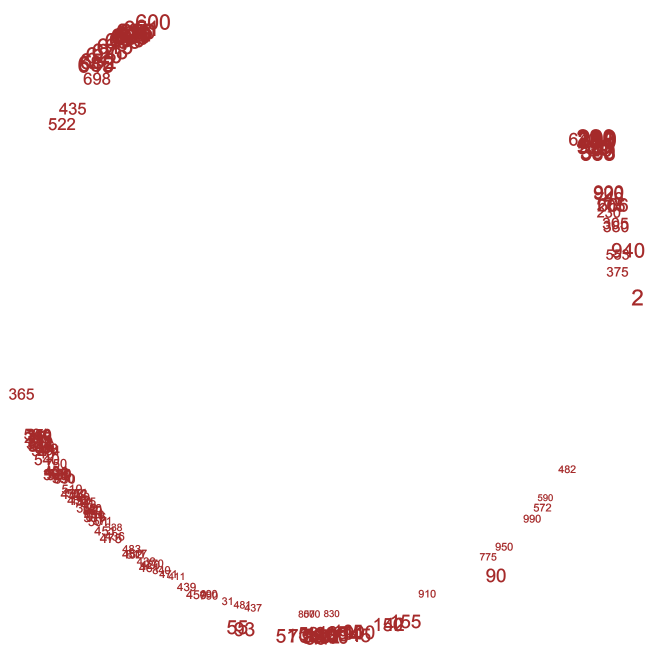

Figure 2: Latent factor plot.

4.1. Face Plausibility

Are states close to who we'd expect them to be?

4.2. Temporal Reliability

Are our measures consistent?

5. Model Competition

5.1. Data, Controls

5.2. In sample explanation

Are coeffs starry and in right direction

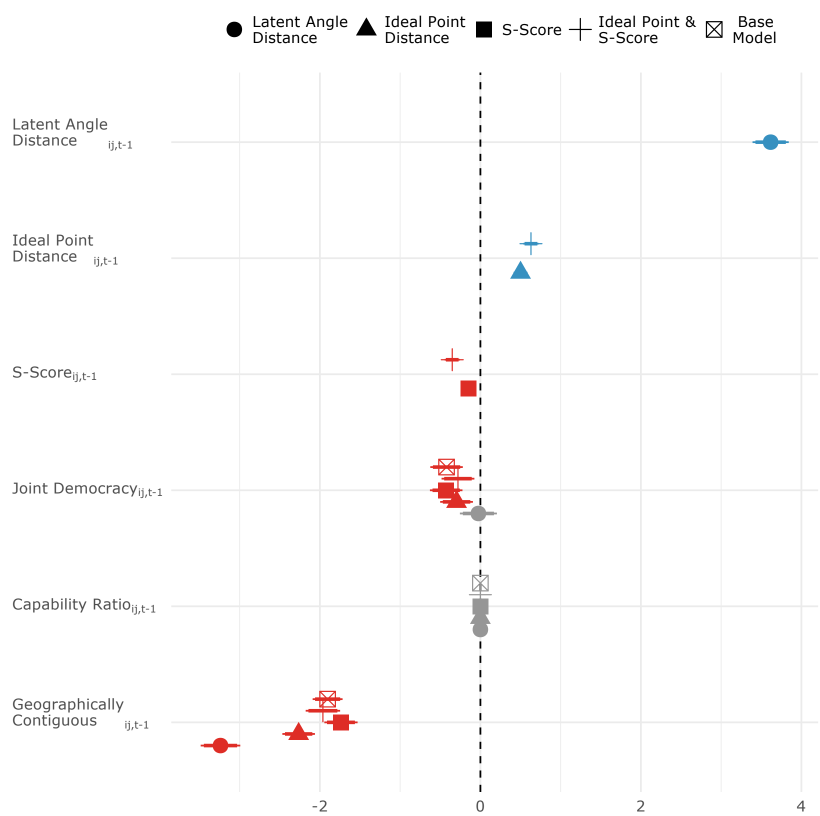

Figure 3: Parameter estimates from models with different measures of state preference. Point represents average estimate, line through the point represents the 95% confidence interval.

5.3. Out of sample prediction

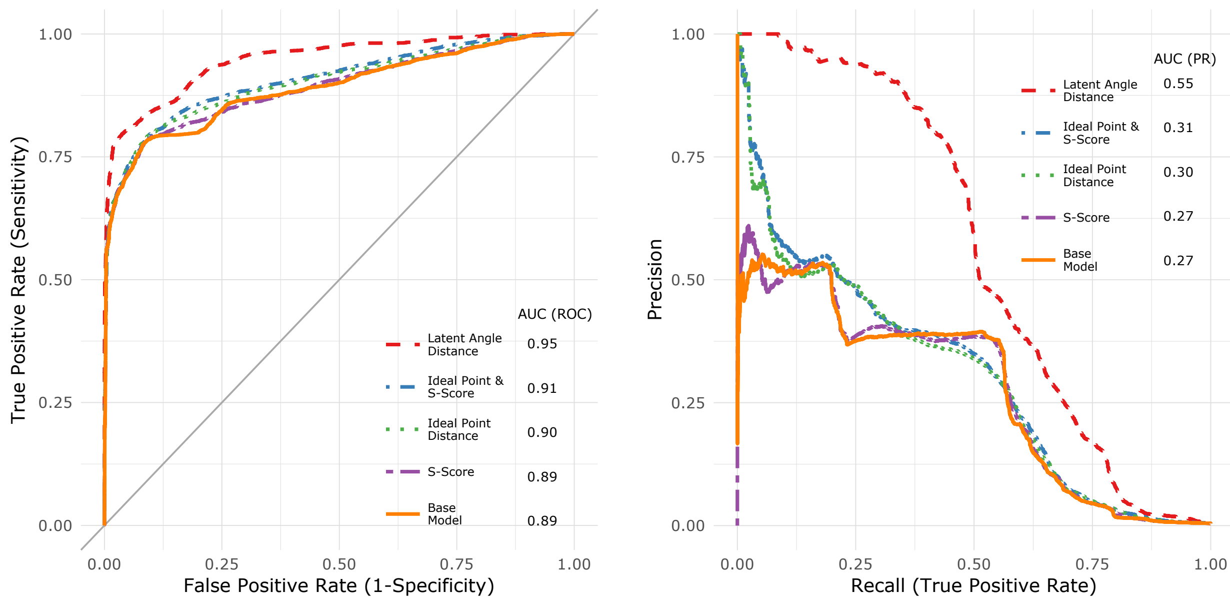

Figure 4: Assessments of out-of-sample predictive performance using ROC curves and PR curves. AUC statistics are provided as well for both curves.

Are we right? Yes.

6. Conclusion

YAY I WAS RIGHT! WE AM SMRT!