

A Latent Factor Approach to Measuring State Preferences

Max Gallop^{a,*}, Shahryar Minhas^b

^a*Departments of Political Science, University of Strathclyde*

^b*Department of Political Science, Michigan State University*

Abstract

State preferences play an important role in international politics. Unfortunately, actually observing and measuring these preferences is impossible. In general, scholars have tried to infer preferences using either UN voting or alliance behavior. The two most notable measures of state preferences that have flowed from this research area are ideal points (Bailey et al., 2017) and S-scores (Signorino & Ritter, 1999). The basis of both these models is a spatial weighting scheme that has proven useful but discounts higher-order effects that might be present in relational data structures such as UN voting and alliances. We begin by arguing that both alliances and UN voting are simply examples of the multiple layers upon which states interact with one another. To estimate a measure of state preferences, we utilize a latent factor model that provides a reduced-rank approximation of the main patterns across the layers. Our new measure of preferences plausibly describes important state relations, and yields important insights on the relationship between preferences, democracy, and international conflict. Additionally, we show that a model of conflict using this measure of state preferences decisively outperforms models using extant measures when it comes to predicting conflict in an out-of-sample context.

*Corresponding author

Email addresses: max.gallop@strath.ac.uk (Max Gallop), minhassh@msu.edu (Shahryar Minhas)

Why we care about preferences

If we want to understand how two states interact in international politics, we need to know how similar their foreign policy preferences are. We can consider each state to have a preferred policy outcome on each possible issue that might arise in international relations. We can conceive of these preferred outcomes as an ideal point in multidimensional space. Given the fact that many issues in international politics are related, we can represent these preferences in far fewer dimensions than there are issues in international politics. These preferences will also change over time. When states have similar preferences on an issue, they will be more likely to collaborate to achieve their joint preference on that issue, and more generally states with similar foreign policy preferences will be cooperative in a larger proportion of their interactions. States with similar preferences are also unlikely to be involved in violent disputes with each other because the policy benefits of these disputes are unlikely to surpass the cost of fighting. Conversely, when states have highly dissimilar foreign policy preferences, cooperation will be difficult and violence will be more common. Unfortunately, while we have abundant data to measure the strength of states' economies, the volume of trade between states, or even their military power, it is much more difficult to measure states' preferences, because they are not observable.

Effectively measuring state preferences would yield scholars a number of benefits. A number of formal theories of international relations require measures of preferences to be tested: the expected utility theory proffered by (Bueno de Mesquita, 1983) has similarity of preferences as an important input. Further attempts to expand studies of crisis bargaining to include mediation (Kydd, 2003), coalitional dynamics (Wolford, 2014), or the possibility of additional disputants (Gallop, 2017) require a measure of state preferences in order to predict whether war will be the result of bargaining failure.

Preferences have been used in empirical studies predicting bilateral trade, foreign aid, stability of international institutions and the incidence of conflict (DeRouen and Heo, 2004; Stone, 2004; Gartzke, 2007; Kastner, 2007; Braumoeller, 2008).

A substantive theoretical reason for why we need a good measure of preferences is to correctly understand the democratic peace. It is difficult to entangle whether democracies avoid war with other democracies because of the intrinsic nature of democracy, or simply because they appear to share similar ends. Farber and Gowa (1995) argue that democracies were only peaceful during the Cold War period because they had similar preferences and alliance structures. Similarly, Gartzke (1998) argues that dissimilar preferences are a necessary condition for conflict. Oneal and Russett (1999) respond by arguing that democracy has both a direct inhibiting effect on conflict, and an indirect one through influencing state preferences.¹ While there has been some impressive development with measures of preferences in recent years, a more accurate measure is essential to disentangle the extent to which peace is the product of shared preferences, and the extent to which institutions and norms are driving peace.

Much of the extant literature has focused on estimating state preferences by utilizing spatial weighting models on either alliance behavior or United Nations (UN) voting scores. These approaches have proven to be useful but there are two reasons to desire a different approach. First, alliances are rare and voting together in the UN is very common, so, by only focusing on the direct dyadic behavior, we risk mischaracterizing important relationships. Second, we would expect a better understanding of state preferences to help us predict state behavior, but as we show in Figure 1 adding measures of state preferences to a traditional model of interstate disputes yields relatively

¹Gartzke (2000) argued that even though democracies might have similar preferences, the residual of preferences from democracy explains conflict much better than the residual of democracy from preferences.

scant increases in terms of predictive ability.

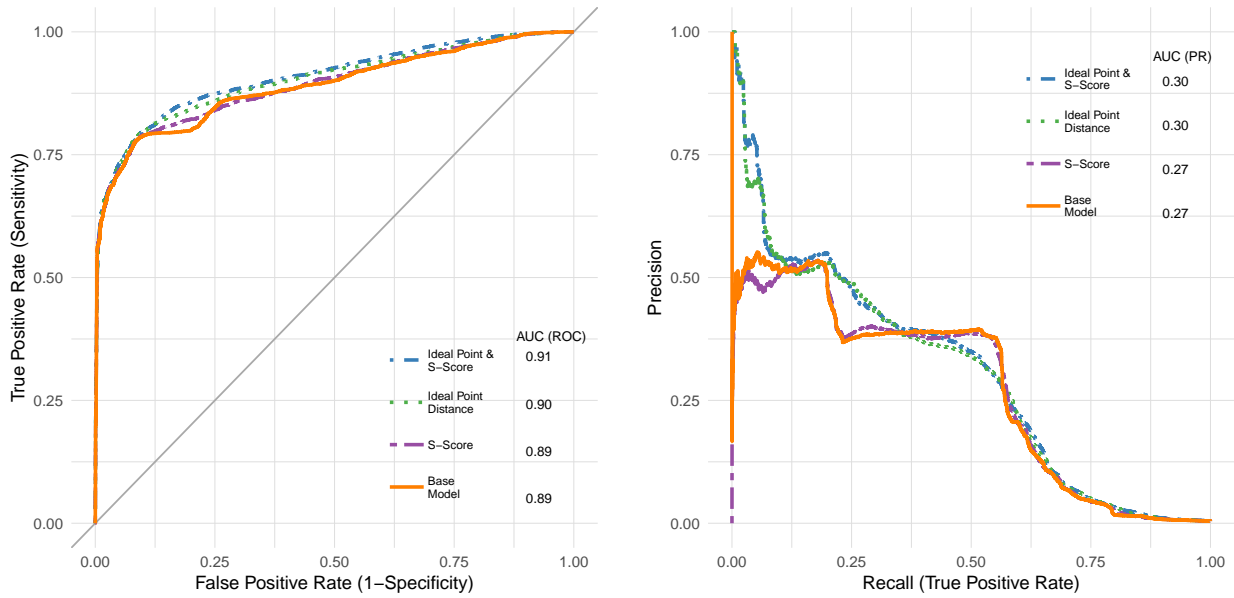


Figure 1: Assessments of out-of-sample predictive performance of Militarized Interstate Disputes using ROC curves and PR curves. AUC statistics are provided as well for both curves.

We can improve on these measures of preferences using the same raw material by acknowledging that both alliance membership and UN voting are layers of relationships that takes place simultaneously and in an interdependent context. Specifically, these relations between states constitute a multilayer network, in which the various layers correspond to different ways states are interacting with one another at a given time point. A bevy of research has shown that accounting for network structure necessitates an approach that can account for the indirect relations states share. As such, we make two contributions to the existing literature on state preferences. We introduce a latent factor model that accounts for higher-order dependence patterns across multiple layers. We show that our revised approach of measuring state preferences both better characterizes relationships that have had counterintuitive results, and this measure greatly enhances our ability to predict instances of conflict.

Sources of Preference Measures: Alliance Portfolios and UN Voting

Given that we cannot directly observe state preferences, scholars have attempted to estimate preferences using two main behavioral indicators: who states choose to ally with and how states vote at the UN. 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. Bueno De Mesquita and Lalman (2008) encapsulate the logic when they note that "alliance commitments reflect a nation's position on major international issues". Measures of alliance behavior do, however, suffer from the fact that these measures are largely static and sparsely occurring. 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 Häge (2011) points out, the fact that links are so rare creates an artificial similarity of alliance portfolios.

We also have a relatively large corpus of 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 (Gartzke, 1998). This is especially fortuitous because the methodology of inferring preferences from voting in a legislature is 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 prone to large supermajorities of the type rarely seen in "ordinary" legislatures.

Current measures of preferences: S-Scores

The initial measure used to measure preference similarity based on alliance portfolios was Kendall's τ_B (Bueno De Mesquita and Lalman, 2008). This measure is:

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

where n_c is the number of pairs where both actor i and j have the same rank ordering (for example both the United Kingdom and the United States are more closely allied to Israel than to Iran), n_d is the number of pairs where they have discordant rankings (the United States 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.

Signorino and Ritter (1999) 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.² The equation for the S-score is:

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

here P^i and P^j are vectors of length N , showing the relation that states i and k have to each of the N states (including themselves). W is a vector of weights (normalized to sum to 1) allowing a scholar to put higher (lower) values of more (less) important

²Bennett and Rupert (2003) also find a stronger relationship between theoretical predictions and results when using S-scores than when using τ_B .

states – allowing relations with China to play a larger role in two states' similarity score than relations with San Marino $d(P^i, P^j, W, L)$ is the distance between portfolio i (P^i) and portfolio j (P^j) based on the vector of weights W and the scoring rule L . If using an absolute distance scoring rule, then $d(P^i, P^j, W, L) = \sum_{k=1}^N \frac{w_k}{\Delta_k^{\max}} |p_k^i - p_k^j|$. In other words, we would calculate the distance between the two portfolios by looking at the absolute distance between each item in the portfolio (p_k^i for state i 's relationship with state k) adjusted by the weight given to this relationship (w_k) and then normalized by the highest possible difference between p_k^i and p_k^j , Δ_k^{\max} . $d^{\max}(W, L)$ is the largest distance between portfolios observed in the policy space, so this means that states at the maximum observed distance will have an S-score of -1 , and those with identical portfolios will have an S-score of 1 . For the weight matrix, generally, analysts have 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 importance, for example using their share of world military capability, as calculated by Singer and Small (1995). Gartzke (1998) attempted to apply a similar S-score methodology to UN voting data and created the “Affinity of Nations” index. An important point 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 in a states preferences 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).

In recent years, many scholars have pointed out that forming and maintaining alliances are not independent dyadic phenomena, but are rather part of an interdependent network (or series of networks). Warren (2010) pointed out how extra-dyadic factors mattered for alliance formations, in particular alliances with allies of your allies

(and enemies of your allies) were more likely. Further investigation uncovered more network effects were important such as popularity and 2-stars (Cranmer et al., 2012b). The strategic nature of states when they form alliance ties leads to interdependence in the alliance network, as states seek to ensure their strength and security as efficiently as possible, privileging ties that complete triangles, and paying attention to the decreasing returns of additional alliances (Cranmer et al., 2012a). Later, Warren (2016) demonstrated not only were network effects (like preferential attachment, density, and transitivity) important in the generation of the alliance network, but the alliance network and the conflict network were mutually constitutive. Similarly, Kinne and Bunte (2018) uncovered links between the network of defense cooperation, and the network of bilateral loans, as states strategically loans to exert policy influence on other states, and strategically formed communities of defense cooperation in order to enhance the power and independence of its members.

An advantage of utilizing UN General Assembly Voting, is that it allowed the field to take advantage of methodological advances that have been made in the study of legislatures (Poole and Rosenthal, 1985). Bailey et al. (2017) 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 state's vote will be based on the latent variable Z_{itv} , representing the preference of state i , on vote v , at time t , defined such that:

$$Z_{itv} = \beta_v \theta_{it} + \epsilon_{iv} \quad (3)$$

Where β_v is the discrimination factor of bill v , determining whether states with high

ideal points will vote yes (if β_v is negative) or no (positive). θ_{it} is state i 's ideal point at time t , and ϵ_{iv} is actor and bill specific error. Of course, we do not observe the latent variable, and only observe the outcome Y_{itv} , which will either be yes, no, or abstention. The model creates a pair of cutpoints γ_{1v} and γ_{2v} in the preference space, such that if $Z_{itv} < \gamma_{1v}$, $Y_{itv} = \text{Yes}$, if $Z_{itv} > \gamma_{2v}$, $Y_{itv} = \text{No}$ and otherwise abstain. This allows the model to use observed vote outcomes in order to determine each states' ideal point in each year.

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 θ_{it} . With these constraints, they solve for the ideal points using a Metropolis Hastings Markov Chain Monte Carlo (MCMC).

Both methods relying on UN data, and those relying on alliances have difficulties distinguishing within 'o's and 'i's. For example, if we know two states are allies, we have reason to believe they have similar preferences, but if we know they are not allies, it is not clear whether they are enemies or they are indifferent – the United States is “not-allies” with both Bhutan and North Korea for example. As of 2012, using the Correlates of War projects alliance data, only about 1/8th of all dyads were between countries with any sort of alliance. Similarly, with UN voting, so many UN votes contain super-majorities and states vote together a huge proportion of the time. If we only look at yes and no votes in the UN general assembly, the median pair of states has voted together about 96% of the time. If we include abstentions, they have voted together 86% of the time. So when two states vote together it is hard to distinguish between states voting together because of similar preferences, or just preferences that are not radically dissimilar. Both S-scores and Item Response theory succeed in adding granularity and nuance to these rough measures, but they are both limited by focusing only on a relationship between two states.

We can see the potential issues of focusing only on direct relations when we view how these two measures of preference treat relations over the Korean peninsula. If we take China, North Korea, South Korea, and the United States, we would expect the United States and South Korea to have preferences that are similar to each other and dissimilar from China and North Korea (and vice versa). Yet, if we look at extant measures of preferences (as of 2012), as depicted in Figure 2, they do not seem to effectively characterize this relationship. S-scores based on alliance portfolios posit that China and the two Koreas are closely clustered, with the United States distant from all three, while ideal point distances put South Korea as equidistant between the United States and North Korea. Now it could be that these measures are producing a novel, counterintuitive, result, but given the failures of extant preference measures to add much to predictive models of conflict, one might be skeptical.

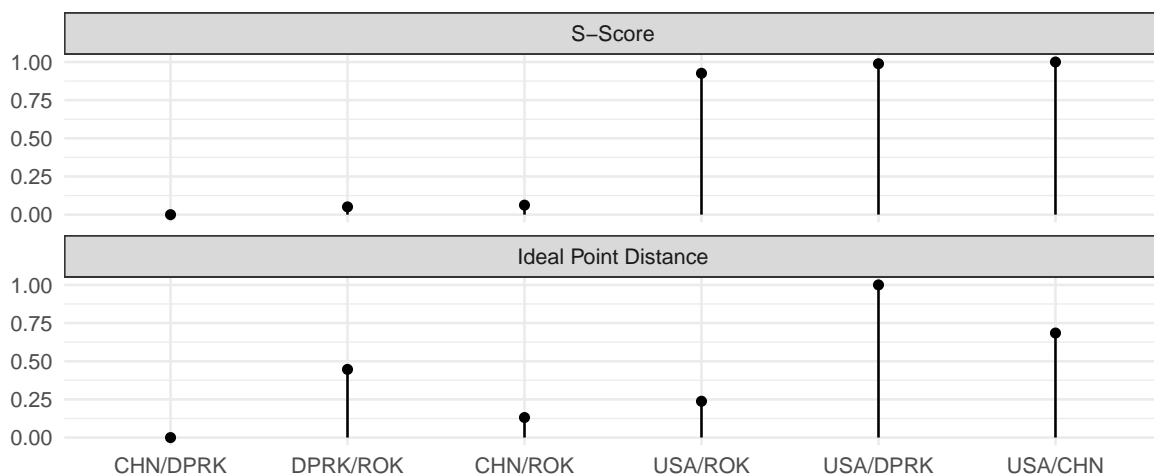


Figure 2: Visualization of ideal point distance and S-score relationships between China (CHN), North Korea (DPRK), South Korea (ROK), and the United States (USA) in 2012. We have rescaled each of these measures to be between 0 and 1 for comparability, where a 1 indicates that states are farther apart and a 0 that states are closer together.

The sources of these surprising results become more clear when looking at the data on which they are based. In 2012, according to the Correlates of War, North Korea only

had 3 alliances – a non-aggression pact with the South, and alliances with Russia and China. Similarly, South Korea's only alliances were that non-aggression pact, and an alliance with the United States. Given the United States' many other allies, there was much more divergence between their alliance portfolio and South Korea's, than there was between the two Koreas' portfolios (Gibler and Sarkees, 2004). Similarly, when looking at voting patterns at the UN, South Korea voted 50% of the time with the US, 63% of the time with North Korea, and 70% of the time with China.

Even using this data, we can better approximate state preferences when we treat alliances and UN voting as relational data. When it comes to alliance behavior, the fact that North Korea was allies with China and Russia, and South Korea with the United States could give us additional information, because the alliance behaviors of countries such as the United States and China are so divergent. When looking at voting patterns at the UN, the need for a relational approach is even more apparent. While South Korea only voted with the US 50% of the time at the UN, this was in the top 15% of all countries in terms of voting with the US, whereas South Korea was in the bottom 20% in terms of the proportion of time voting with China.

We thus argue that two changes can substantially improve measures of state preferences. First, both alliances and UN voting contain information about state foreign policy preferences, and given the limits of this information, we should find a way to use both. Second, by using network techniques and treating this data as relational data, we can wring more information from the stone, and get both a more nuanced, and more accurate view of state affinity and state preferences.

Synthesizing Measures of State Preference

The approach that we introduce here to measure state preferences starts by assuming that both UN voting and alliance relationships are sources of information on how

states relate to one another on the international stage. By accounting for the multiple layers upon which states interact with one another we can synthesize a better measure of state preferences than if we relied on any one measure alone.³ The downside of this extant approach, however, is that it does not account for structural patterns that we often see in relational data.

Relational data is composed of observations between pairs of actors, or dyads. For both alliance relationships and UN voting, we are able to observe how the actors in the international system interact with one another across time. This system of interactions taken in its totality defines a network, and within these types of structures a bevy of research has shown that we need methods that go beyond assuming that interactions are taking place between just two actors in a vacuum (Wasserman and Faust, 1994; Snijders and Nowicki, 1997). As such we reformulate the problem of determining state preferences in terms of a network analysis. The goal of our approach is summarized in Figure 3. In the top row, we represent UN voting and alliance patterns at time t as a pair of adjacency matrices that form a multiplex.⁴ This multiplex represents the relations between states across two dimensions, and our goal is to extract a lower dimensional representation that accounts for the types of interdependencies that occur in networks. The end result then will be a single $n \times n$ matrix, where n represents the number of actors, in which the cross-sections denote our estimates of the similarity of preferences between two countries.

We generate these estimates through a latent variable framework that relies on a matrix decomposition to estimate a Gaussian score for each country pair. We will

³The 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).

⁴The approach that we describe here can be generalized to a multiplex with more than two dimensions.

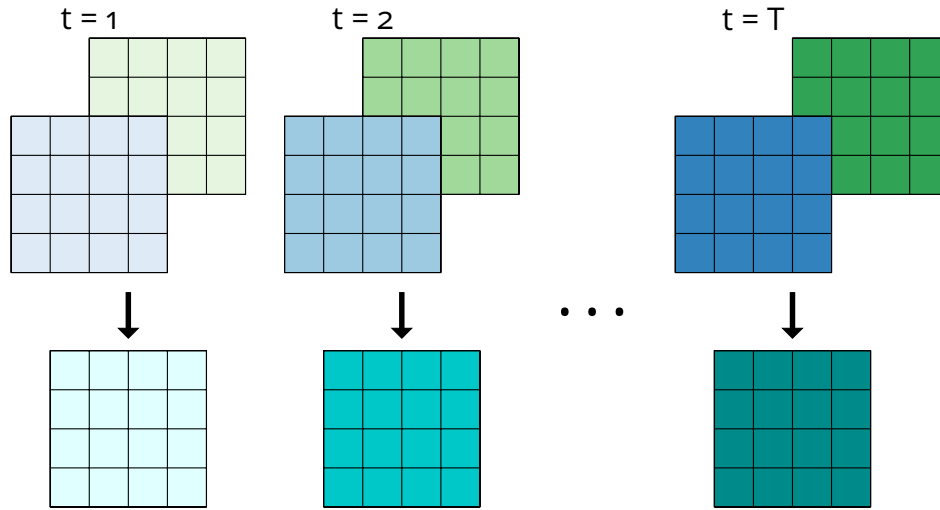


Figure 3: The green and blue colors represent different relational measures and darker shading indicates later time periods. Our goal is to reduce the patterns found across those layers of relationships into a single measure.

show that by combining different measures of state preferences, and better accounting for network dependencies through our approach, we are able to generate a measure for preference that maintains the insights of both UN voting scores and S-scores and which can yield new insights, in particular when it comes to predicting and explaining interstate conflict.

Latent Factor Model

In essence, our goal here is to measure an unobservable concept. This is a problem that is very familiar in political science and a number of techniques based on latent variable models have been developed to study political ideology (Martin and Quinn, 2002; König et al., 2013), human rights abuses (Fariss, 2014), and judicial independence (Linzer and Staton, 2015). Obviously, the ideal points measure developed by Bailey et al. (2017) also follows in this growing practice of extracting unobserved information via latent variable modeling. Here we employ this general framework to develop a latent measurement of how a state relates to other states in a network context. The factor

analysis we employ seeks to take as an input the interactions that actors have with others across a variety of dimensions and project this onto a low-dimensional space. In many ways this goal is no different than how others have sought to find simpler representations of legislators and bills (Poole and Rosenthal, 1985; Clinton et al., 2004).

However, in the network case there are specific types of patterns that often occur and that should be captured when reducing the dimensionality of a network. One such pattern is stochastic equivalence. Stochastic equivalence refers to the idea that there are communities of nodes in a network, and actors within a community act similarly towards those in other communities. Thus the community membership of an actor provides us with information on how that actor will act towards others in the network. Put more concretely, a pair of actors i, j are stochastically equivalent if the probability of i relating to, and being related to, by every other actor is the same as the probability for j (Anderson et al., 1992). This concept simply speaks to the assertion that we can learn something about how an actor will interact with an entire network based on, for example, the existing set of alliances that they are enmeshed in.

An additional dependence pattern that often manifests in networks is homophily – the tendency of actors to form links they share some latent attribute. In many cases, homophily will lead to greater levels of transitivity in a network because, if i and j share an attribute and thus are more likely to be linked, and j and k share the same attribute and are linked, then we should expect to see a link between i and k . In the context of clustering in alliance relationships, we are likely to find that states like the United States, United Kingdom, and Germany may cluster together because they share some latent state level attribute. We would ignore salient information if we did not use, for example, the United Kingdom's behavior towards third parties, when trying to understand the United States' preference similarity with those parties. Doing so is likely to paint an incomplete picture of the preferences that states share with one another.

We account for higher order dependence patterns using a latent factor model (LFM) that allows us to capture both concepts discussed above: the tendency of actors to assort themselves into groups and to form transitive links (Hoff, 2005; Hoff et al., 2013; Minhas et al., 2018). Using the LFM ensures that similarity in preferences are likely to be transitive, for example, if the United States has similar preferences to the United Kingdom, and the United Kingdom to France, the United States' preferences should be relatively close to France's. Further the most useful feature of the LFM for our purpose is that it places actors it summarizes the interdependencies between actors in a relational k -dimensional latent vector space. Thus, the model we use does a better job of capturing the interdependencies in both alliance and voting data than we would expect from the literature. From this space we can not only approximate how pairs of countries relate to one another, but also estimate how an actor may relate to a cluster of other actors or the international system as a whole. Actors that have vectors pointing in similar directions are more likely to have similar state preferences based on their alliances and UN voting records. The angle between the vectors for actors i and j provides an estimate of how similar the state preferences of i are to j .

To generate this measure, scholars would begin by constructing T different $n \times n \times p$ arrays, where T represents the number of periods, n represents the number of actors,⁵ and p the number of observed variables used to synthesize a measure of state preference. For the application that we focus on in the next section, both alliance relationships and UN voting scores are undirected measures, meaning that $y_{ij} = y_{ji} \forall p$ and t .⁶ In order to obtain a lower-dimension relational measure of state preferences, we use the LFM separately for each time point:

⁵The number of actors can vary by period.

⁶The approach we describe can also be generalized to the case where $y_{ij} \neq y_{ji}$.

$$Y = f(\theta)$$

$$\theta = \beta^\top X + Z$$

$$Z = M + E$$

$$M = U\Lambda U^\top, \text{ where}$$

$$u_i \in \mathbb{R}^k \text{ and}$$

$$\Lambda \text{ is a } k \times k \text{ diagonal matrix}$$

where $f(\cdot)$ is a general link function corresponding to the distribution of Y and $\beta^\top \mathbf{X}$ is the standard regression term for dyadic and nodal fixed effects. In this application, for the sake of parsimony we abstain from using fixed effects. However, if one was interested in estimating a measure of preference that parsed out the effect of geographic distance between i and j , for example, than this could be accomplished within the context of this framework by simply including that as a covariate in the X design array. Z represents any additional patterns in data unrelated to the specified dyadic and nodal fixed effects. To incorporate multiple measures of similarity into a single ideal point estimation, we treat each different slice of data as arising from a common distribution. In this way, each additional observed relationship between actors that we add serves to provide additional information to the model that can be used to estimate a latent measure of state preference.

The key part of this model lies in the decomposition of Z . Specifically, we can write $Z = M + E$ such that the matrix E represents noise, and M is systematic effects. By matrix theory, we can factorize M into the product of two simpler matrices: $M = U\Lambda U^\top$, where $u_i \in \mathbb{R}^k$ is a latent vector associated to node i and Λ is a $k \times k$ diagonal

matrix. Thus under this framework a vector of latent characteristics are estimated for each actor, $u_i = \{u_{i,1}, \dots, u_{i,k}\}$. Similarity in the latent factors between two actors, $u_i \approx u_j$, corresponds to how stochastically equivalent they are and the diagonal entries in Λ , $\lambda_k > 0$ or $\lambda_k < 0$, determine the level of homophily (or antihomophily) in the network (Minhas et al., 2018). Within this framework, the LFM can represent either positive or negative homophily in varying degrees and stochastically equivalent actors may or may not share strong relationships with others in their “community”.⁷

Inference of the latent vectors for each actor takes place within the context of a MCMC procedure that enables us to construct approximate samples from the posterior distributions of the latent variables. For the latent factor model, a diffuse normal prior is placed on Λ and the prior distribution on U is taken to be a uniform distribution. The MCMC proceeds by sampling the parameters from their full conditional distributions for each k : sample $\{u_i, \dots, u_n\}$ from a multivariate normal distribution and then sample Λ from its multivariate normal distribution.

The key output from the LFM for our purpose here is $U\Lambda U^\top$. Actor positions in the latent factor space are characterized by the concepts of homophily and stochastic equivalence discussed above. Interpretation of this space needs to be done with care. Distances between actors cannot be interpreted using Euclidean metrics, as actor’s latent positions are actually embedded within a k -dimensional hypersphere. This means that an actor’s vector direction within the k -dimensional hypersphere indicates which latent preferences an actor i has and does not have. Comparing the similarity of preferences between two states, $\{i, j\}$, can be accomplished by comparing the direction to which their respective factor vectors point. A commonly used metric for this sort

⁷This model does assume, once we condition on the latent factor $U\Lambda U^\top$, that relations are independent, but this factor has been found to capture the different dependencies that have been theorized to be present in both alliance and voting behavior.

of problem in the recommender system literature from computer science is the cosine of the angle formed by the latent vectors of both actors.⁸ We refer to this distance metric as latent angle distance.⁹ Thus, if the estimated latent vectors of two states are in the same direction, they are apt to have both alliances and UN co-voting to similar partners. 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.

Data Sources, Modeling choices

We use the LFM with $k = 2$ to generate a combined measure of state preference similarity that accounts for network effects. As inputs, we use the UN voting similarity index (Voeten, 2013)¹⁰ and number of alliance relationships between states by time t (Gibler and Sarkees, 2004). However, to facilitate comparison between the metrics, we first standardize and normalize these two measures. This gives us an $n \times n \times T \times 2$ array, where the first two dimensions represent countries, the third dimension is the year, and the fourth is the particular measure of similarity. The item at index (1,2,1,1) would be the transformed value of the number of alliance relationships for countries i and j at the first year of our data, similarly (1,2,1,2) would be the UN voting similarity index.

With this data, we run an LFM with a Gaussian link, and in particular we use the $U\Lambda U^\top$ term produced by each yearly model to estimate each states position in a two-dimensional hypersphere. We then evaluate whether there is additional utility gained from using this latent angle position, as compared to the similarity of alliance portfolios

⁸For a review of this literature see (Xavier Amatriain and Pujo, 2015).

⁹This measure is defined as: Latent angle distance $_{ij} = \frac{u_i \cdot u_j}{\|u_i\| \cdot \|u_j\|}$.

¹⁰Specifically, the “agree3un” variable.

and UN ideal point distance measures.

Face Plausibility

An important question for these different measures of preferences, are whether they give results that “make sense.” In particular, we would hope that the measure both provides plausible levels to relationships – sorting states into friends and foes effectively – and that when these measures change, they do so in ways that correspond to changes in the world. One of our principle critiques of both alliance portfolio S-scores and UN voting based ideal points is that they describe certain important relationships in a way that some may find implausible. Using our measure we return to the example of relationships in East Asia in 2012. We find that our latent angle measure, depicted in figure 4, corresponds much better to conventional understanding of the relations between these states.

To generalize this test of face plausibility, we present all three measures’ accounts of six dyadic relationships over time.¹¹ Additionally, we rescale each of these measures to be between 0 and 1 for comparability, where a 1 indicates that states are farther apart and a 0 that states are closer together.

We first look at three close relationships where we would expect to see similar preferences. Figure 5 depicts the relationships between France and Germany, the US and Israel, and North Korea and China. In all three cases our measure using latent angle distance has consistently low values – nearly 0 in the case of France and Germany, and China and North Korea, and low but less stable values for the US/Israel relationship. Alliance S-Scores correctly classifies Franco-German and Sino-North Korean friendship, while the US/Israel relationship is characterized as being relatively neutral. The mea-

¹¹For the sake of having each measure operate in the same direction, we transform the S-score such that the value shown is $1 - S$. Thus for all three variables, 0 implies perfect symmetry of preferences.

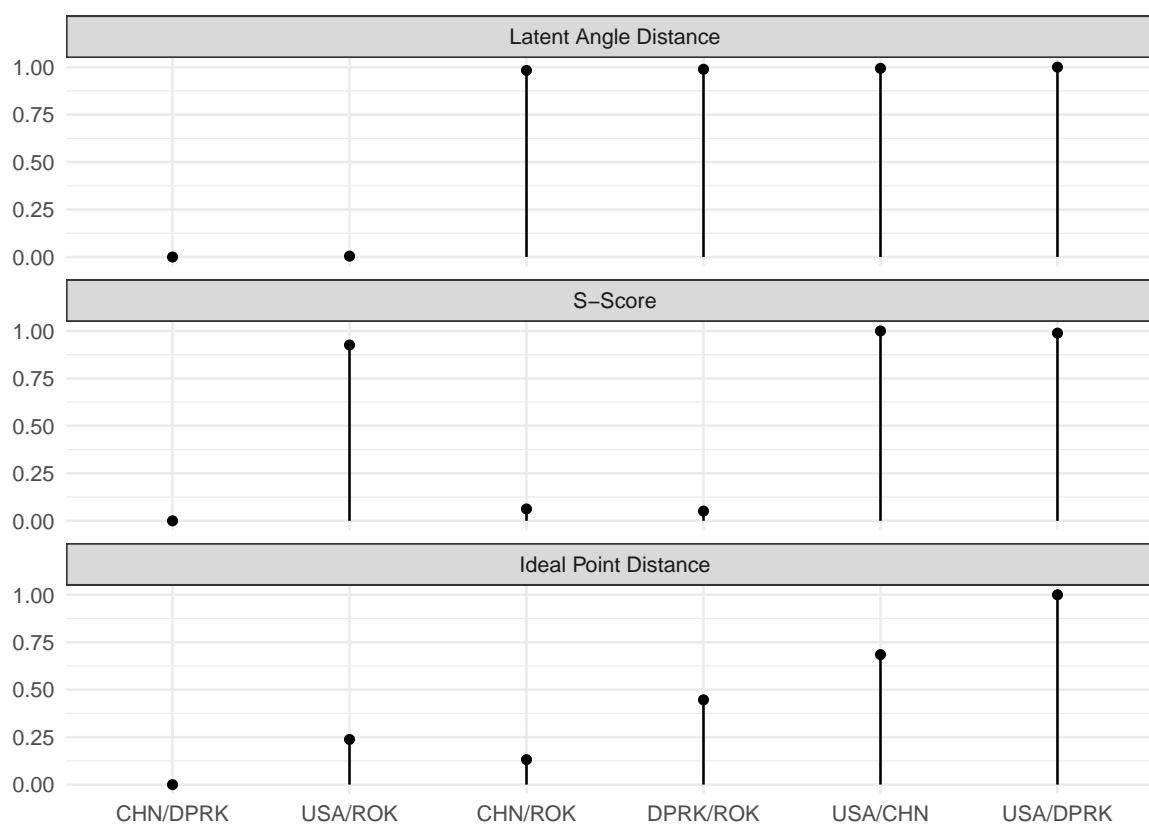


Figure 4: Visualization of ideal point distance, S-score, and latent angle relationships between China (CHN), North Korea (DPRK), South Korea (ROK), and the United States (USA) in 2012. We have rescaled each of these measures to be between 0 and 1 for comparability, where a 1 indicates that states are farther apart and a 0 that states are closer together.

sure based on UN voting is most out of step in terms of characterizing these relationships, with notable divergence in the preferences of many of these pairs.

In figure 6 we look at the United States' relationship with three countries that are characterized by change and major events. S-scores are the only measure that does not detect a marked improvement in the US/Russian relationship at the end of the Cold War. Both the UN ideal points and latent Angle space find significant improvements followed by a drift toward enmity, whereas S-scores have a constant (though slightly improving) neutral relationship. For the US and Iraq no measure depicts more similar preferences following the US occupation, though only latent angle distance finds an

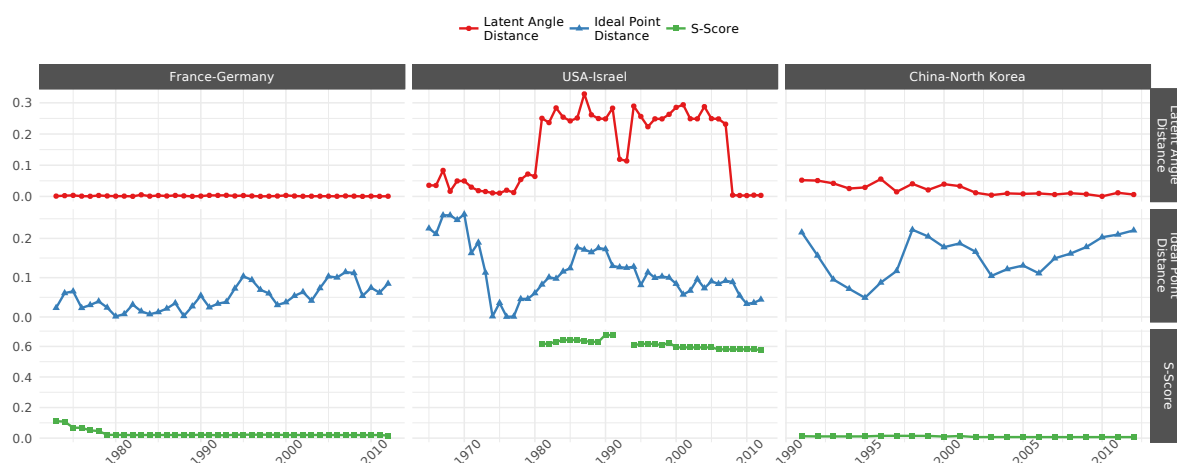


Figure 5: Dyadic relationships between France-Germany, United States-Israel, and China-North Korea according to the different preference measures. Yearly latent angle distances between dyads are denoted by red circles, ideal point distance based on UN voting in blue triangles, and S-scores by green squares. Note that we have rescale each of these measures to between 0 and 1, where a 1 indicates that states are farther apart and a 0 that states are closer together.

increase in enmity in the run-up to the United States' invasion. Finally, for the US and China, the S-score has a consistent neutral relationship, while both UN ideal points and latent angles both have more negative relationships, and more variance – with the latent angles metric finding particularly large spikes at the beginning of the Bush and Obama administrations.

As can be seen from these relationships, the measure of preferences based on latent angle distance is in many cases as plausible or more than incumbent measures of preferences. While the measure has more temporal instability than S-scores or UN ideal points, in these six cases it often does better, and rarely worse at conforming to our expectations of the relationships. Of course, this could just be a case of us picking particularly propitious cases. Next, we conduct a the large-N analysis of conflict and compare the added utility of these various measures of state preferences.

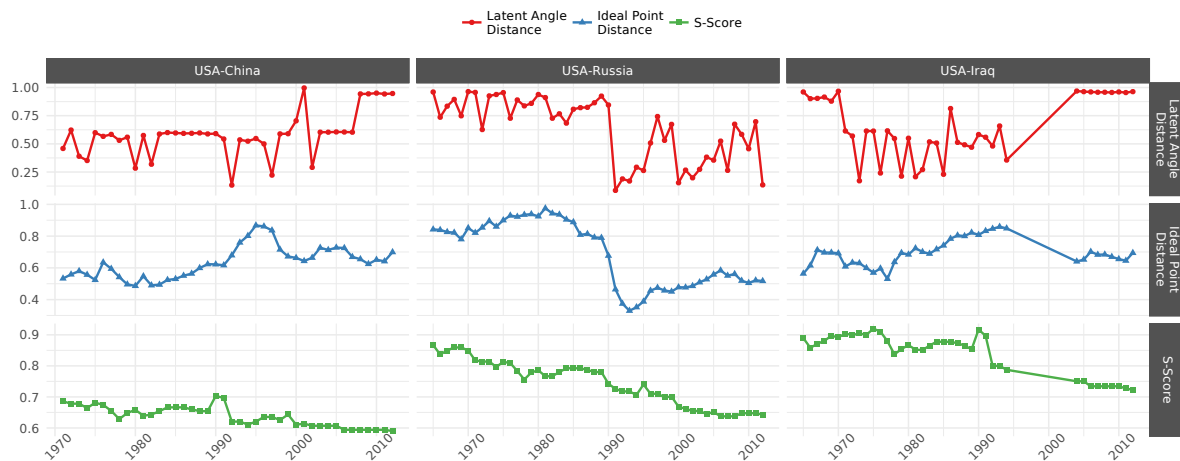


Figure 6: Dyadic relationships between United States-China, United States-Russia, and United States-Iraq according to the different preference measures. Yearly latent angle distances between dyads are denoted by red circles, ideal point distance based on UN voting in blue triangles, and S-scores by green squares. Note that we have rescale each of these measures to between 0 and 1, where a 1 indicates that states are farther apart and a 0 that states are closer together.

Model Competition

To evaluate the different measures of state preferences, we assess their utility in predicting the occurrence of interstate disputes. Here we look at four non-nested models: a model using no measures of state preferences, one using an S-Score based on similarity in alliance portfolio (Signorino and Ritter, 1999), one using the ideal points determined by UN voting (Bailey et al., 2017), a model using both UN ideal points and alliance S-scores, and finally, a model using our latent angle approach that combines the raw data from UN voting and alliances. We evaluate the models on two criteria: whether state preferences have a consistent effect in the predicted direction, and how well each model does at predicting disputes in an out-of-sample context.

In each of these models, we utilize a logistic regression of Militarized Interstate Dispute (MID) participation on measures of state preferences and a vector of control variables. These control variables overlap with the standard framework used in O'Neal and

Russett's canonical work on the democratic peace (Oneal and Russett, 1997).¹² In particular, we include a binary measure of joint democracy (whether both states have Polity IV scores ≥ 7), whether the states are contiguous, and the ratio of state capabilities as measured by the Correlates of War Project's Composite Index of National Capabilities (CINC). We also account for temporal interdependence using a peace year spline (Carter and Signorino, 2010).

In-sample explanation

As detailed in figure 7, two of the measures of state preferences perform as we would expect. Our measure of state preference using latent angle difference is highly significant and positive: states with more dissimilar preferences will have greater difference in their latent angles, and this is highly associated with a greater risk of conflict. Similarly, UN ideal point distance passes this test. The measure using UN voting ideal points is positive and clearly distinct from 0, indicating that states with more distant ideal points, and thus more dissimilar preferences, are more likely to find themselves in conflict. On the other hand, higher alliance S-scores are consistently associated with higher probabilities of conflict – so states with more similar preferences as measured using alliance portfolios are more likely to quarrel. This is, to say the least, surprising. These results hold when those measures of preference are used in isolation, or in tandem.

The models have one major difference in terms of the controls: in the model using latent angle distance, joint democracy is indistinguishable from 0. This is particularly interesting as one of the major criticisms of democratic peace theory is that democracies have similar preferences. Some argue that it is similarity in preferences that leads to

¹²The exception is that our models ignore trade interdependency, as including that data drastically decreases the number of observations.

peace among democracies. Despite this dispute, most attempts to include preferences in the standard democratic peace regressions still find a consistent pacifying effect of democracy. (as do those models with UN voting and S-scores presented here). With our measure of preferences, however, democracy's effect is negligible. More research is necessary to disentangle whether the criticism is now credible, but work such as this provides a template for us to parse out the effect of democracy versus preferences on conflict.

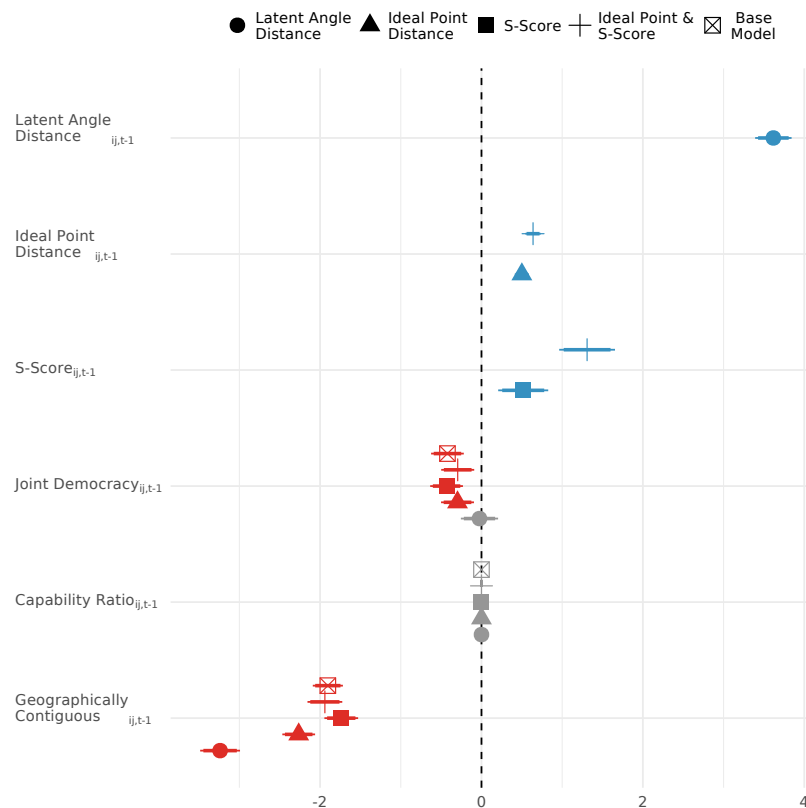


Figure 7: Parameter estimates from models with different measures of state preference. Point represents average estimate, line through the point represents the 95% confidence interval.

Out-of-sample prediction

Given these results, we can say that two of the measures of preferences behave as we would expect, while S-scores do not. To adjudicate between the two measures of

preference similarity that pass this test, and help determine what we should make of the differing effect of democracy, we turn to out-of-sample prediction. We undertake a cross-validation procedure in which we partition our data into 30 different folds. This process works by taking each fold, k , and running a logistic model excluding data from that fold. Once we have parameter estimates from a model that excluded fold k , we predict the probability of a MID in fold k using only the parameter estimates and the covariates from fold k .

We then compare the performance of these models using two metrics: area under the Receiver Operator Characteristic Curve (AUC-ROC) and the Precision Recall Curve (AUC-PR). The ROC curve examines the tradeoff between true positives and false positives, and the PR examines the tradeoff between making only correct predictions and predicting all the disputes that occurred. In general, the ROC will disproportionately reward those models that predict 0 well – and we can interpret the ROC as the likelihood a prediction is correct. The numeric value for the PR has less of a clear interpretation, but models with a higher PR do a better job of predicting when events actually occur.

As shown in figure 8, the model using latent angle distance decisively outperforms all the other models. While the AUC-ROC is somewhat higher with the latent Angle model, the real difference between the measures shines through in the AUC-PR, where the model using this measure performs twice as well as the base model. In contrast, models using other measures of state preferences yield only minimal improvements in prediction over the base model. This is especially relevant because AUC-PR specifically focuses on the difficult task of predicting conflict, compared to the relatively easier task of predicting non-conflict that is rewarded by the AUC-ROC measure. Thus we have reason for confidence in both the usefulness of this measure of state preferences and renewed reason for skepticism in the effect of joint democracy once we control for state preferences.

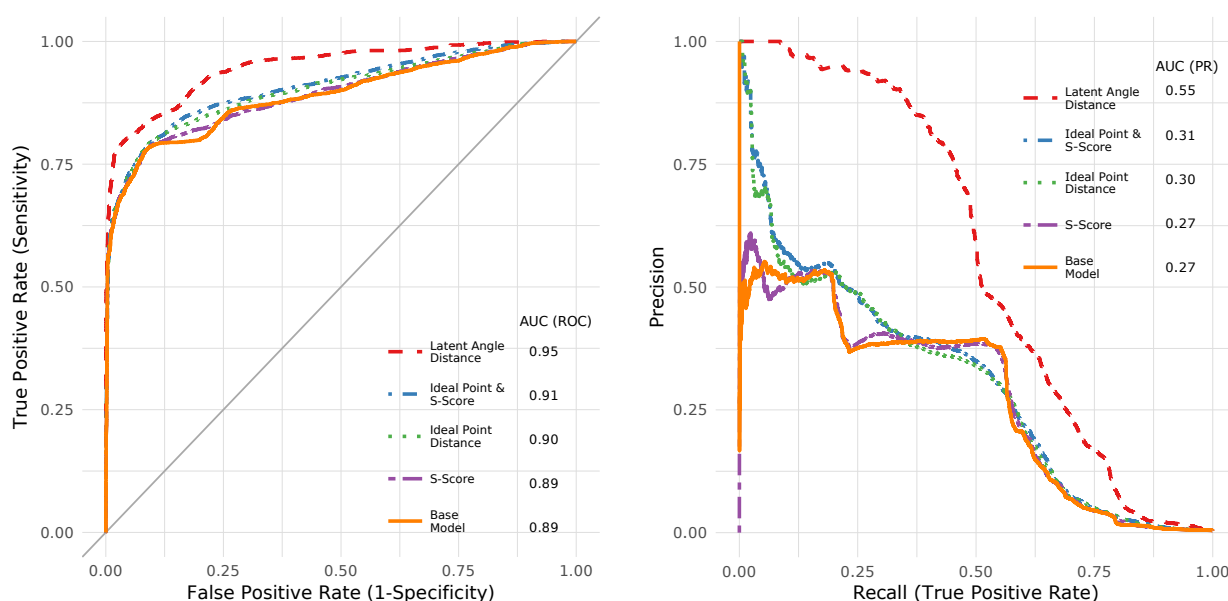


Figure 8: Assessments of out-of-sample predictive performance using ROC curves and PR curves. AUC statistics are provided as well for both curves.

Conclusion

We use a network methodology to create a new measure of state preferences using both UN Voting data and alliance data. This measure of state preferences demonstrates face plausibility comparable or superior to existing measures when it comes to capturing the dynamics of a number of notable dyadic relationships. We then attempt to use this measure of state preferences in a predictive model of interstate disputes. In doing so, we find that the measure of preferences has the expected effect (states with similar preferences are less likely to be involved in disputes) and inclusion of our measure leads to the measure of joint democracy becoming indistinguishable from 0. Most importantly, a model of interstate conflict that includes our measure of preferences decisively outperforms models that include both of the most prominent existing measures of preferences.

While this measure of state preferences has yielded leverage in predicting conflict,

it should also be useful in answering a number of other questions. One possible use would be to look at the measure of state preferences as an outcome variable, rather than a predictor. We could here look at how preferences change in tandem with leadership change – can we find evidence, for example, that the election of Donald Trump moved the United States’ foreign policy preferences away from the major Western European states and towards Russia’s? We could also see how well this measure of state preferences predicts more collaborative behavior – treaty membership or trade for example.

Finally, this particular method allows us to control for confounding fixed effects. A closer examination of the relationship between democracy, preferences, and conflict could create a measure of the component of state preferences not explained by democracy.¹³ Similarly, the underlying methodology could be usefully applied to other questions. For example, it could be used to estimate the alignments of elites in non-democratic states or even as a way of combining a number of related variables on development or democracy.

Ours is not the first paper to use network analysis to attempt to measure a theoretically important but difficult to observe phenomenon. For example, Moody and White (2003) measured social cohesion by looking at the minimum number of paths connecting each actor in a group (and applied to high school friendship networks and among American businesses. A similar approach, by Beardsley et al. (2018) generates a measure of hierarchy by looking at a network of arms transfers and first finding the clusters in each group, then how central an actor is within a given cluster, they go on to use this measure of hierarchy in a downstream model to explain interstate conflict, and similarly Cranmer et al. (2012b) use a measure of multiplex modularity in the network

¹³We look at the entire measure of state preferences because our primary goal here is not to examine this relationship, but to create the most accurate measure of preferences possible.

of alliances, trade, and international organization membership to measure “Kantian fractionalization”—the extent to which the international system is fragmented between liberal and illiberal states—which predicts the aggregate level of violence. Where we differ from this work, however, is that while previous attempts at measurement using networks have relied on descriptive statistics of observed networks, we use a Latent Factor approach which assumes that the network we study is observed with error from the true data-generating process. In cases where the network is observed accurately, and measurement directly flows from this network, our approach is unnecessary and selection of appropriate descriptive statistics should suffice for measurement. However, in many cases, especially in the social sciences, we either observe the true network with error, or we select a network as a proxy for the true process we want to measure.

In addition to helping us to understand state preferences, this sort of technique could help in measuring phenomenon like social cohesion and hierarchy, or spatial contagion. If one wanted to use a latent network approach to measure social cohesion, one could potentially do this with a Latent Class Model like in ?. Using some measure of social interaction, this model would give the probability that each member is in a particular clique or subgroup in society. We could then look at how many members of society have probability of membership in multiple groups above a certain threshold to see how many individuals bridge different groups, contributing to social cohesion in the way that Moody and White (2003) measured it. In understanding how phenomenon – violence, diseases, new technology to name a few examples – diffuse, many scholars rely on spatial lag models, which require the scholar to specify a spatial weights matrix that indicates how likely a phenomenon is to move from one area to another. Of course, we can never know the true adjacency matrix, and so scholars use a proxy, most often some form of geographic distance. We can (and in the case of political violence have) improved the predictive performance of spatial models by inferring

a weights matrix using a latent network approach based on how the phenomenon has diffused in the past.

If a latent network approach is needed, the specific type used should depend on the problem.¹⁴

¹⁴For more information on different types of latent networks, see Minhas et al. (2018) or Goldenberg et al. (2010). If your beliefs about the true data-generating process you wish to measure are that it is about membership in disjoint groups, and you have a strong prior on the number of extant groups, a Latent Class Model (see Airoldi et al. (2008)) will clearly measure the probability of membership in these groups, and as Goldenberg et al. (2010) note, it is the easiest model to interpret. However, many phenomena cannot meet the assumption of the Latent Class Model. The Latent Space Model popularized by Handcock et al. (2008) is another model where results are easy to interpret, and requires less assumptions and priors about the data-generating process, but if you wish to measure something related to homophily or stochastic equivalence, this model will not capture those. As Goldenberg et al. (2010)[p.179] note, the latent factor model (which we use) "can capture more connectivity patterns than the latent class and the latent distance models for a given degree of model complexity...There is a price to pay, however. The eigenmodel is the least amenable to interpretation among the three models." Regardless of the model used, if you are trying to use a latent network model for measurement, and especially if you are using the measure in a downstream model, you need to be aware of and account for uncertainty. To do this, we suggest running the downstream model repeatedly with different draws from the distribution for the latent space, then combining the models using Rubin (1976)'s rules to obtain an estimate of the effect of your measure that accounts for uncertainty.

- Airoldi, E. M., Blei, D. M., Fienberg, S. E., Xing, E. P., 2008. Mixed membership stochastic blockmodels. *Journal of Machine Learning Research* 9 (September), 1981–2014.
- Anderson, C. J., Wasserman, S., Faust, K., 1992. Building stochastic blockmodels. *Social Networks* 14 (1), 137–161.
- Bailey, M. A., Strezhnev, A., Voeten, E., 2017. Estimating dynamic state preferences from United Nations voting data. *Journal of Conflict Resolution* 61 (2), 430–456.
- Beardsley, K., Liu, H., Mucha, P. J., Siegel, D. A., Tellez, J., 2018. Hierarchy and the provision of order in international politics. Tech. rep., Working paper, Duke University.
- Bennett, D. S., Rupert, M. C., June 2003. Comparing measures of political similarity: An empirical comparison of S versus τ_b in the study of international conflict. *Journal of Conflict Resolution* 47 (3), 367–393.
- Braumoeller, B. F., 2008. Systemic politics and the origins of great power conflict. *American Political Science Review* 102 (1), 77–93.
- Bueno de Mesquita, B., 1983. *The War Trap*. Yale University Press, New Haven, CT.
- Bueno De Mesquita, B., Lalman, D., 2008. *War and reason: Domestic and international imperatives*. Yale University Press.
- Carter, D. B., Signorino, C. S., 2010. Back to the future: Modeling time dependence in binary data. *Political Analysis* 18 (3), 271–292.
- Clinton, J., Jackman, S., Rivers, D., May 2004. The statistical analysis of roll call data. *American Political Science Review* 98 (2), 355–370.
- Cranmer, S. J., Desmarais, B. A., Kirkland, J. H., 2012a. Toward a network theory of alliance formation. *International Interactions* 38 (3), 295–324.

- Cranmer, S. J., Desmarais, B. A., Menninga, E. J., 2012b. Complex dependencies in the alliance network. *Conflict Management and Peace Science* 29 (3), 279–313.
- DeRouen, K., Heo, U., 2004. Reward, punishment or inducement? US economic and military aid, 1946–1996. *Defence and Peace Economics* 15 (5), 453–470.
- Farber, H., Gowa, J., 1995. Politics and peace. *International Security* 20 (2), 123–146.
- Fariss, C. J., 2014. Respect for human rights has improved over time: Modeling the changing standard of accountability. *American Political Science Review* 108 (2), 297–318.
- Gallop, M., 2017. More dangerous than dyads: How a third party enables rationalist explanations for war. *Journal of Peace Research*.
- Gartzke, E., 1998. Kant we all just get along? Opportunity, willingness, and the origins of the democratic peace. *American Journal of Political Science* 42 (1), 1–27.
- Gartzke, E., 2000. Preferences and the democratic peace. *International Studies Quarterly* 44, 191–212.
- Gartzke, E., 2007. The capitalist peace. *American Journal of Political Science* 51 (1), 166–191.
- Gibler, D. M., Sarkees, M., March 2004. Measuring alliances: The correlates of war formal interstate alliance data set, 1816–2000. *Journal of Peace Research* 41 (2), 211–222.
- Goldenberg, A., Zheng, A. X., Fienberg, S. E., Airolidi, E. M., et al., 2010. A survey of statistical network models. *Foundations and Trends® in Machine Learning* 2 (2), 129–233.
- Häge, F. M., 2011. Choice or circumstance? Adjusting measures of foreign policy similarity for chance agreement. *Political Analysis*, 287–305.

- Handcock, M. S., Hunter, D. R., Butts, C. T., Goodreau, S. M., Morris, M., 2008. `statnet`: Software tools for the representation, visualization, analysis and simulation of network data. *Journal of Statistical Software* 24 (1), 1548.
- Hoff, P. D., 2005. Bilinear mixed-effects models for dyadic data. *Journal of the American Statistical Association* 100 (4690), 286–295.
- Hoff, P. D., Fosdick, B., Volfovsky, A., Stovel, K., 2013. Likelihoods for fixed rank nomination networks. *Network Science* 1 (3), 253–277.
- Kastner, S. L., 2007. When do conflicting political relations affect international trade? *Journal of Conflict Resolution* 51 (4), 664–688.
- Kinne, B. J., Bunte, J. B., 2018. Guns or money? defense co-operation and bilateral lending as coevolving networks. *British Journal of Political Science*, 1–22.
- König, T., Marbach, M., Osnabrügge, M., 2013. Estimating party positions across countries and time—a dynamic latent variable model for manifesto data. *Political Analysis* 21 (4), 468–491.
- Kydd, A., 2003. Which side are you on? Bias, Credibility, and Mediation. *American Journal of Political Science* 47 (4), 597–611.
- Linzer, D. A., Staton, J. K., 2015. A global measure of judicial independence, 1948–2012. *Journal of Law and Courts* 3 (2), 223–256.
- Martin, A. D., Quinn, K. M., 2002. Dynamic ideal point estimation via markov chain, monte carlo for the U.S. Supreme Court, 1953–1999. *Political Analysis* 10 (2), 134–153.
- Minhas, S., Hoff, P. D., Ward, M. D., 2018. Inferential approaches for network analysis: AMEN for latent factor models. *Political Analysis*.

- Moody, J., White, D. R., 2003. Structural cohesion and embeddedness: A hierarchical concept of social groups. *American sociological review*, 103–127.
- Oneal, J., Russett, B. M., 1999. Is the liberal peace just an artifact of cold war interests? Assessing recent critiques. *International Interactions* 25 (3), 213–241.
- Oneal, J. R., Russett, B. M., 1997. The classical liberals were right: Democracy, interdependence, and conflict, 1950-1985. *International Studies Quarterly* 41 (2), 267–293.
- Poole, K. T., Rosenthal, H., 1985. A spatial model for legislative roll call analysis. *American Journal of Political Science* 29 (2), 357–384.
- Rubin, D. B., 1976. Inference and missing data. *Biometrika* 63 (3), 581–592.
- Signorino, C., Ritter, J., 1999. Tau-b or not tau-b. *International Studies Quarterly* 43 (1), 115–144.
- Singer, J. D., Small, M., 1995. National Military Capabilities Data. *Correlates of War Project*, Ann Arbor, MI.
- Snijders, T. A., Nowicki, K., 1997. Estimation and prediction for stochastic blockmodels for graphs with latent block structure. *Journal of Classification* 14 (1), 75–100.
- Stone, R. W., 2004. The political economy of IMF lending in Africa. *American Political Science Review* 98 (4), 577–591.
- Voeten, E., 2013. Data and analyses of voting in the United Nations. Routledge, Ch. 4.
- Warren, T. C., 2010. The geometry of security: Modeling interstate alliances as evolving networks. *Journal of Peace Research* 47 (6), 697–709.

- Warren, T. C., 2016. Modeling the co-evolution of international and domestic institutions: Alliances, democracy, and the complex path to peace. *Journal of Peace Research* 53, tbd.
- Wasserman, S., Faust, K., 1994. *Social Network Analysis: Methods and Applications*. Cambridge University Press, Cambridge.
- Wolford, S., 2014. Showing restraint, signaling resolve: Coalitions, cooperation, and crisis bargaining. *American Journal of Political Science* 58 (1), 144–156.
- Xavier Amatriain, Alejandro Jaimes, N. O., Pujo, J. M., 2015. Data mining methods for recommender systems. In: *Recommender Systems Handbook*. Springer, pp. 227–262.