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The Future of US Alliances and Partnerships: A Data Science Approach

Nilanthi Samaranayake, Vincent Bauer, Cornell Overfield

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Abstract

This is the report for the CNA-Initiated study, The Future of US Alliances and Partnerships: A Data Science Approach. The project aims to explore the potential for how data science could help shed light on a complicated issue in international security relations, potentially generating new and actionable recommendations for US policy-makers. This file documents our data assembly and modeling methods, results of our data tabulations, and implications and caveats of our findings. We conclude by outlining future research tasks from this dataset for use by US policy-makers.

This document contains the best opinion of CNA at the time of issue.

For questions about this study, contact Nilanthi Samaranayake (project director) at nilanthi@cna.org.

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Approved by: **September 2021**

Eric V. Thompson, Vice President and Director
Strategy, Policy, Plans, and Programs Division

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Executive Summary

The subject of US alliances and strategic partnerships is becoming more salient in the era of strategic competition. Although policy-makers and academics devoted considerable effort to the study of US alliances during the Cold War, the topic receded in attention over the past two decades. Now, in the current environment of US threat perceptions from China and Russia, academics and policy-makers are reorienting their gaze to the great power competition that looks to dominate US international interests for the foreseeable future.

High-level officials recognize the role that alliances and partnerships serve in advancing US interests. For example, President Joe Biden traveled to Europe for his first overseas trip, which included a summit of the North Atlantic Treaty Organization (NATO) alliance. Secretary of State Antony Blinken held his first diplomatic meetings with neighboring Mexico and Canada through virtual interaction. In the Indo-Pacific region, the previous Trump administration resurrected the senior-level "Quad" discussions between the US, Japan, Australia, and India. Through these high-profile interactions, US policy-makers have signaled that alliances and partnerships will remain central to US global interests.

Because of the increased need to understand the role of alliances and partnerships in an era of strategic competition, US policy-makers need to modernize their tools for conducting analysis. This study aims to draw on rising interest in Big Data and apply data science methods to the long-standing topic of alliance management for advancing US national security interests. To this end, CNA is building linkages between academic disciplines and developing a more rigorous and traceable understanding of US alliances and partnerships to inform US policy-makers.

In this report, we provide select findings from this exploratory research effort and recommend caution when interpreting results about future relationship outcomes. This includes acknowledging the assumptions that went into model development and the subjective nature of variable selection, as with all models.

Keeping these caveats in mind, we assembled datasets with key international security indicators, built machine-learning models, and derived the following results about the future of alliances and partnerships.

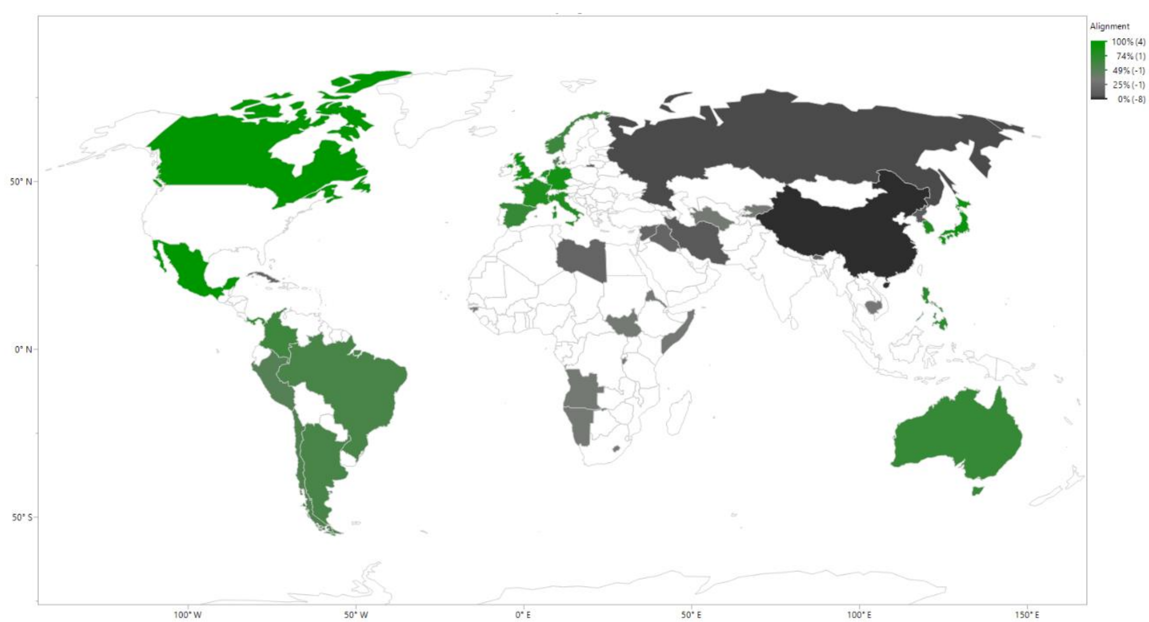
Findings

Drawing on various datasets, using machine-learning approaches, and incorporating several key indicators, we developed an index of current alignment strength that allows us to identify the countries with the strongest and weakest alignment with the US.

- Canada and Mexico top the list of countries most aligned with the US, while China is the *least* aligned with the US.
- For the 20 countries most closely aligned with the US, all are connected through a bilateral or multilateral alliance treaty (e.g., NATO, the Inter-American Treaty of Reciprocal Assistance, the Australia, New Zealand and United States Security Treaty).
- No African or Middle East countries are in the top 20.
- Four of the five US treaty allies in the Indo-Pacific are in the top 20.
- Few countries in the Americas and Europe are listed in the bottom 20.

Figure 1 visualizes the top and bottom 20 alignment scores on a world map.

Figure 1. Choropleth map: international alignment with the US



Source: CNA Alliances dataset, 2021. Based on 2016 figures.

In addition to characterizing the strength of alliances today, we also built a machine-learning model that predicts the strength of American alliances with international partners up to five years into the future.

- Predicted alignment strength (produced by the model) correlates with alignment strength scores that were calculated for the previous index. Forecasting the future state of alliances would allow policy-makers to be proactive, rather than reactive, in strengthening international relationships.
- US alignment strength with Singapore, United Arab Emirates, Namibia, Benin, and Lesotho today is *lower than predicted,* based on countries with similar characteristics. This model can provide useful information for US policy-makers about expected trends in international relationships, especially where important US interests, such as military basing rights, are at stake.

This project represents an initial effort at establishing a new, rigorous method of studying the future of US alliances and partnerships in what appears to be a decades-long era of strategic competition. Future research using this data offers the prospect of studying how an alliance or partnership might change in response to changes in underlying conditions (such as a coup or revolution bringing about a change in a country's domestic political system, or the imposition of economic sanctions and the effect on imports and exports) and potential opportunities for further investment and relationship building.

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Introduction

This project is a research effort on the future of US alliances and strategic partnerships. We aim to explore how data science can help shed light on a complicated issue in international security relations, potentially generating new and actionable insights for US policy-makers. We conclude that data science methods provide value to inform policy-makers on the current state of US alliances and partnerships, and reveal potential gaps to address in the future management of these relationships that are critical for US national security.

To this end, a multidisciplinary team of CNA analysts[1] is collaborating to link academic fields and develop a more rigorous and traceable understanding of US alliances and partnerships.

Project context

Over the past few years, great power competition (GPC) with China and Russia has become the organizing principle behind US national strategy, as seen in recent, high-level strategy documents from the White House and Department of Defense (DOD). The 2017 National Security Strategy (NSS) states that "great power competition returned."[2] In support of the NSS, the National Defense Strategy (NDS) unclassified summary discusses the "reemergence of long-term strategic competition."[3] Indeed, the first line of effort in the NDS, "Build a More Lethal Force," identifies lethality as a priority for the US defense strategy. In support of the NDS, the 2018 National Military Strategy (NMS) also discusses the GPC problem set.[4] Because of this sharp focus on great power threats, policy-makers have gained much insight into US adversaries.

[1] From CNA's Strategy, Policy, Plans, and Programs Division (Strategy and Policy Analysis Program) and CNA's Data Science Division (Data Science Predictive Analytics Program).

[2] The White House, *National Security Strategy of the United States of America*, Dec. 2017, 27, https://trumpwhitehouse.archives.gov/wp-content/uploads/2017/12/NSS-Final-12-18-2017-0905.pdf.

[3] Department of Defense, *Summary of the 2018 National Defense Strategy of the United States of America: Sharpening the American Military's Competitive Edge*, Jan. 2018, 2, https://dod.defense.gov/Portals/1/Documents/pubs/2018-National-Defense-Strategy-Summary.pdf.

[4] The Joint Chiefs of Staff, *Description of the National Military Strategy 2018*, July 2019, 2, https://www.jcs.mil/Portals/36/Documents/Publications/UNCLASS_2018_National_Military_Strategy_Description.pdf.

Why alliances?

Much of the recent discourse and analysis of GPC has focused on adversaries to the detriment of the second line of effort in the NDS, which identifies the importance of strengthening alliances and attracting new partners.[5] The NSS stresses the importance of alliances, partnerships, and coalitions to address great power challenges.[6] Moreover, the 2018 NMS builds on the NDS and highlights the "unique contributions of allies and partners [as] a strategic source of strength for the Joint Force."[7]

The need to strengthen alliances is a critical topic that warrants increased attention in a GPC era. For example, questions are being raised about the future of US access in locations such as the Philippines, as are concerns about the strategic alignment of long-standing partners, such as Argentina, with strengthening economic ties to China. These issues highlight the importance of nurturing long-standing partnerships, as well as seeking new ones, as the strategic conditions shift.

US policy-makers and academics are turning their attention increasingly to the topic.[8] In October 2020, the secretary of defense announced the initiation of the department's Guidance for Development of Alliances and Partnerships (GDAP), which coordinates strategy for American allies and partners. This guidance helps build out the second pillar of the NDS by detailing various aspects of alliances and partnerships and providing useful examples (e.g., key leader engagement, International Professional Military Education, Foreign Military Sales).[9] At the military service level, the tri-service maritime strategy *Advantage at Sea*, released in December 2020, emphasizes that alliances and partners are priorities for the US Navy, Marine Corps, and Coast Guard: "Alliances and partnerships remain our key strategic advantage. Our

[5] *National Defense Strategy*, 8.

[6] *National Security Strategy*, 1, 26, 37.

[7] *National Military Strategy*, 3.

[8] Mira Rapp-Hooper, *Shields of the Republic: The Triumph and Peril of America's Alliances*, Cambridge: Harvard University Press, 2020.

[9] Secretary of Defense Dr. Mark T. Esper, "Secretary of Defense Allies and Partners Remarks at Atlantic Council," Oct. 20, 2020, https://www.defense.gov/Newsroom/Speeches/Speech/Article/2388205/secretary-of-defense-readiness-remarks-at-atlantic-council/source/GovDelivery.

allies, partners, and alliances such as NATO are an enduring asymmetric advantage over our rivals."[10]

The new Biden administration's early announcements suggest continued, if not increased, attention to alliances and partnerships.[11] The March 2021 Interim National Security Strategic Guidance (INSSG) does not use the GPC phrase as the previous administration did; however, it similarly discusses the environment of "strategic competition" in which the US finds itself.[12] Given this continued climate, it states the following goal: "We will reinvigorate and modernize our alliances and partnerships around the world."[13]

The prospect of building on the implementation of recent US strategy documents such as the NDS, GDAP, and INSSG motivates our project to provide clarity on current and future US alliances and strategic partners.

Why data science?

In addition to highlighting why studying alliances is important, we should also discuss why data science methods are appropriate to do so. Much of the important research on alliances is qualitative and theoretical. Social scientists cannot manipulate the phenomenon of "alliances" and their components (e.g., geography, policies, the attitudes of decision-makers) and compare them against control cases, as physicists might do in labs. Sometimes researchers can isolate quasi-experimental conditions in the real world, but these opportunities are rare.

For many people, data science conjures images of Facebook or Google, but it can also help inform political science and the study of alliances—even offering a tool for prediction. Data science can be defined as analytic techniques for prediction based on complex pattern recognition within large-scale, dynamic datasets. We see this contribution in many real-world examples informed by advancements in the underlying techniques over the last few decades, especially by the commercial sector. For example, AlphaZero, the newest generation of chess-playing computer, handily beat traditional chess computers by predicting and responding to their next moves with only a few hours of training. In medicine, Google LYNA (short for Lymph

[10] US Navy, Marine Corps, and Coast Guard, *Advantage at Sea: Prevailing with Integrated All-Domain Naval Power*, Dec. 2020, 6, https://media.defense.gov/2020/Dec/17/2002553481/-1/-1/0/TRISERVICESTRATEGY.PDF/TRISERVICESTRATEGY.PDF.

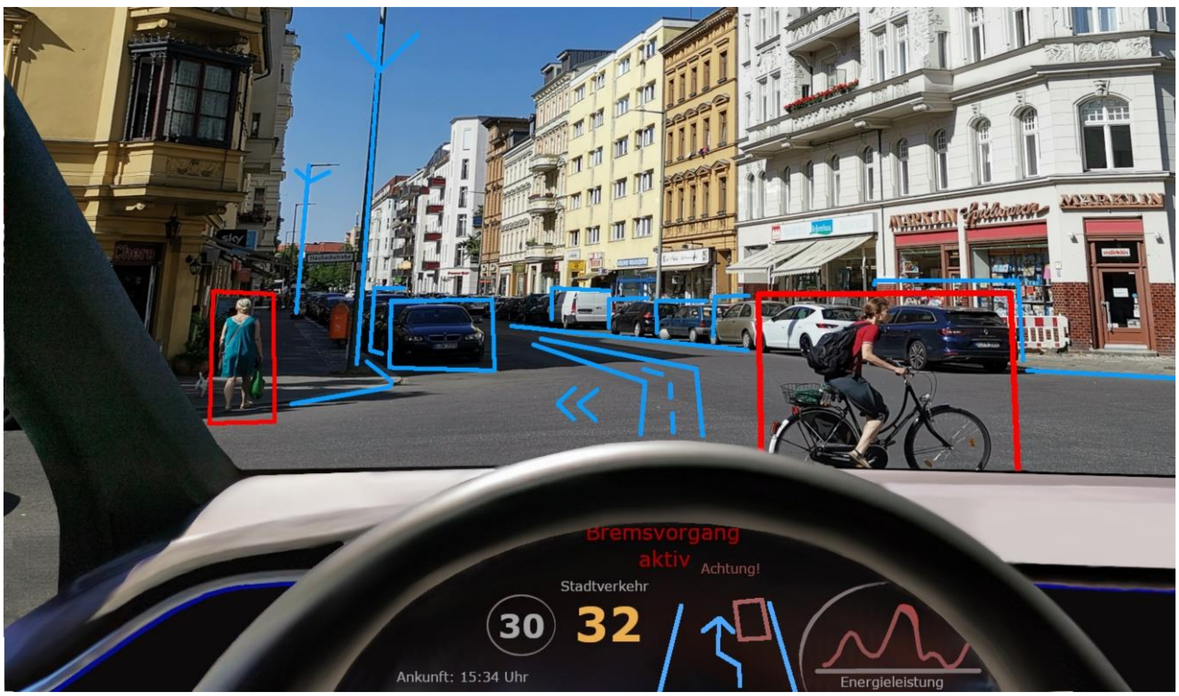
[11] The White House, "The Biden-Harris Administration Immediate Priorities," Jan. 2021, https://www.whitehouse.gov/priorities.

[12] The White House, *Interim National Security Strategic Guidance,* March 2021, 19-20, https://www.whitehouse.gov/wp-content/uploads/2021/03/NSC-1v2.pdf.

[13] Ibid, 10.

Node Assistant) has developed computer visions algorithms and can accurately identify cancer with 99 percent accuracy based on images of lymph node biopsies using its machine-learning algorithm. Moving from the realm of science fiction to a reality within a relatively short time span, self-driving cars use machine learning to recognize objects and forecast the paths of pedestrians and cars. Finally, Internal Revenue Service multidimensional taxpayer profiles forecast individual tax returns, with differences between real and forecasted returns flagged for auditing. Figure 2 illustrates the outcome of data science's machine-learning techniques that enable a self-driving car to interpret its surrounding in a detailed manner (e.g., recognizing cars, pedestrians, and lane directions).

Figure 2. View from within a self-driving car



Source: Eschenzweig, "Picturization of self-driving car from drivers perspective, active breaking and obstacle reconnaissance," Feb. 14, 2020, https://commons.wikimedia.org/wiki/File:Autonomous-driving-Barcelona.jpg.

Methodology

The study of alliances is a wide-ranging topic, and we seek to use innovative methods to analyze alliances and partnerships at a timely moment. Traditional approaches to the study of alliances, such as International Relations (IR) theory, and area studies have generated valuable insights into factors that influence state behavior. For example, the popular neorealist IR theory adopts a systems approach to explanations of international politics and makes predictions about the balance of power in a system of international states.[14]

Yet, new data science methods offer the prospect of examining and predicting state behavior, based on analysis of myriad data on events at different times and under different conditions, as has been conducted in analysis of millions of games of chess (although IR is many times more complex than chess is). For this reason, we believe that there is an opportunity to apply data science techniques to the study of alliances.

Defining alliances vs. partners

Before beginning our examination, defining key terms is critical. IR theorist Stephen Walt defines an *alliance* as "a formal or informal arrangement for security cooperation between two or more sovereign states."[15] He acknowledges taking an intentionally broad approach to this definition and uses *alliance* and *alignment* interchangeably in his analysis. Walt contrasts *alliances* with *formal alliances*, which invoke legal and defense responsibilities. There are understandably fewer formal alliances than there are alliances in which states align with each other informally.

This study will broadly examine countries' strength of alignment with the US, rather than examining only formal alliances. For clarity when interpreting the results, however, we will distinguish between *alliances* and *partnerships*. This distinction reflects the general understanding of international relationships in widely available US government strategy documents.

An intuitive set of definitions from the DOD website distinguishes between *alliances* and *partnerships*:

[14] Kenneth Waltz, "Neorealism: Confusions and Criticisms," *Journal of Politics & Society* 15, No. 1 (2004), 6, https://ir101.co.uk/wp-content/uploads/2018/11/Waltz-Neorealism-Confusions-and-Criticisms.pdf.

[15] Stephen M. Walt, *The Origins of Alliances,* Ithaca: Cornell University Press, 1987, 12.

- "Alliances are formal agreements between two or more nations. In national defense, they're promises that each nation will support the other, particularly during war."
- "Partnerships are less formal than alliances. Often called 'strategic partnerships,' they help build relationships between nations or organizations like militaries. Like alliances, they benefit the members of the partnership, but they can be short-term and don't involve a treaty."[16]

Research questions

As an entry point, we frame our research around three study questions:

1. How can we measure the strength of US security alignment with other countries?
2. What factors and characteristics of a nation correlate with alignment strength with the United States?
3. Can we predict which alliances and partnerships will be advantageous for US policy-makers to pursue?

First, we will consider a foundational research question: How can we measure the strength of US alliances and partnerships? Drawing on a CNA dataset consisting of variables related to the concept of alignment, the study team will build a machine-learning model to examine how these variables relate to each other across the countries of the international system and over a three-decade timeframe.

Second, we will delve deeper and examine the factors and characteristics associated with these strong relationships. To this end, the study team will employ the data science methods of Bayesian factor analysis and Elastic Net regression.

Third, we will examine whether a machine-learning model can help predict whether particular relationships are worth pursuing by US policy-makers. Doing so will help fill gaps in thinking about alliances and add data science as a potential tool for understanding current and future alliance management issues. We will view this issue through the lens of US government policy-makers, with particular interest in the applicability to the DOD.

[16] Claudette Roulo, "Alliances vs. Partnerships," Department of Defense, March 22, 2019, https://www.defense.gov/Explore/Features/story/Article/1684641/alliances-vs-partnerships.

Analytic assumptions and scope

Before conducting this study, we need to identify our analytic assumptions. First, we operate within the dominant IR state-centric paradigm. Therefore, our units of analysis are states, reflecting state-to-state level alliances and partnerships. For instance, we are not considering US ties with non-state actors or supranational bodies such as multilateral institutions (e.g., the European Union).

The topic of US international relationships is wide, varying across multiple dimensions. Therefore, we scope our inquiry to the realm of security through a focus on US alliances and partnerships, as defined earlier. For example, China deserves special note as a country in this analysis. Despite having a significant amount of *economic* interaction with the US, China has been publicly identified as a *strategic* competitor by US government strategy documents. Because our study aims to focus on the security dimension of international relations, we carefully evaluated the inclusion of variables, such as economic factors, in our models that may produce results that are at odds with, for example, the reality of deterioration in US-China strategic relations over the past decade. Those decisions are described in our findings below.

Analytic approach

As this is an exploratory effort, we conducted cursory background research and then launched our analytical process of examining US alliance and partnership strength. In doing so, we:

1. **Identified relevant factors** that may enable or limit alliances and partnerships. This process was informed by accessing publicly available datasets (e.g., defense agreements with US allies and strategic partners, US development assistance,). By relying on these datasets, we offer the caveat that important dimensions exist that are not readily measurable or lack available data. Given our resource constraints, we focused on the most accessible, off-the-shelf variables.
2. **Evaluated our hypotheses** about the components of alliance and partnership strength. To this end, we performed a data analysis on the identified variables to determine correlations for US bilateral alliances and partnerships.
3. **Considered the causes** for correlational findings of strong alliances and partnerships. To this end, we examined select critical cases (e.g., key outliers) and refined our set of variables based on these insights.
4. **Forecasted the alliances and partnerships** that are trending toward strong relationships. To this end, we used data science methods to develop a predictive model to identify close US alliances and partnerships over time.

Data science methods

Beyond linear and logistic regression, more complex data science techniques typically allow researchers to create more accurate and precise predictions and classifications that otherwise cannot be achieved. How can we use data science methods to measure the strength of US alliances? Although defense treaties are one convenient metric, these formal pacts change slowly and cannot capture more nuanced changes in relationship strength. Moreover, other aspects of security alignment beyond the narrow framing of defense pacts might be appropriate to capture, such as the level of international trade and the extent of diplomatic exchange. It is unclear how much weight should be assigned to any of these factors when measuring alignment strength.

Unsupervised machine learning

- Purpose: Measures alignment today
- Method: Bayesian factor analysis
- Caveat: No way to verify that the correlations we are measuring reflect our concept of "alignment"

Supervised machine learning

- Purpose: Predicts alignment tomorrow
- Method: Elastic Net regression
- Caveats: Risk of making imprecise predictions, using an outdated model, and missing variables in the explanation

To solve these problems, we will use Bayesian factor analysis to identify the hidden patterns behind these manifestations of alignment strength and produce a single consistent measure. This method is useful for ranking countries and exploring how each of these factors contributes to alignment strength. However, this approach has a potential shortcoming—although the method uncovers a common dimension that explains how defense pacts, trade, and diplomatic presence move together, there is no way to measure objectively whether this common dimension is what we mean by alignment.

Beyond measuring alignment strength today, policy-makers also need to predict how alignment is likely to evolve in the future and identify high-value opportunities for building alliances and partnerships. For these goals, we use an Elastic Net regression to (1) predict future alignment strength based on historical trends across alliance partners, and (2) identify alignments that are weaker than expected based on a country's particular characteristics. Caveats of this approach are: (1) predictions will have associated confidence intervals for any estimate; (2) our model may become outdated for evolving, real-world circumstances; and (3) the characteristics that we *did not* include in our study might explain why the alignment is weaker than expected.

Data sources

We identified readily available datasets to provide a set of metrics for examining the strength of various US alliances and partnerships. Data sources are listed in Table 1:

Table 1. Project data sources

Data	Source
• Trade volumes • Formal defense and neutrality agreements • Border contiguity • National material capabilities • Militarized interstate disputes	Correlates of War
• Diplomatic representation	Diplometrics
• Population	World Bank
• US arms sales and transfers	Stockholm International Peace Research Institute (SIPRI)
• Regime type • Civil liberties • Corruption • Gender equality • Rule of law	Varieties of Democracy (V-Dem) project
• US diplomatic agreement count	US State Department
• US foreign aid	US Agency for International Development (USAID)
• Free-ness	Freedom House
• Geographic region	United Nations (UN) Statistics Division
• Interstate economic sanctions	University of North Carolina: Threat and Imposition of Economic Sanctions (TIES)
• Interstate cyberattacks and incidents	Dyadic Cyber Incident and Dispute (DCID) Data
• GDP per capita	University of Groningen: Maddison Project
• Democracy-Autocracy spectrum	Center for Systemic Peace: Polity IV

Source: CNA. A total of 16 datasets were used (4 Correlates of War + Diplometrics + State Department + USAID + SIPRI + TIES + DCID + V-Dem + 5 others through V-Dem: UN, Maddison, World Bank, Polity IV, Freedom House).

The research team assembled these data sources into a dataset to conduct correlational analysis. The team needed to address data quality problems, which was a time-consuming process. For example, we needed to standardize country names and restructure several data sources into a dyadic country-year observation format. To produce our findings, we used the cleaned, merged dataset to explore the relationships between various metrics and alignment strength.

Findings: Measuring Alignment Strength

Our first research question is: "How can we measure the strength of US security alignment with other countries?" This section lays out our analytical process, our findings, the implications of these findings, and the caveats on interpreting our findings.

Analytical process: What did we do?

To answer this question and build a measure of alignment strength, we first needed to examine the degree of alignment between the US and the countries in our dataset. Our data science approach uses unsupervised machine learning, which uncovers groupings based on common features in the data. With this model, our goal is to build a measure of US alignment strength rather than explain what drives countries to become allies. For example, we did not provide the model with a dependent variable for finding correlations.

- Built unsupervised machine learning model to measure historical alignment patterns and produce synthetic alignment metric
- Method: Bayesian factor analysis
- Tool: R software

To this end, the study team employed a Bayesian factor analysis model.[17] Of the factors in our dataset, the study team chose five variables because they demonstrate engagement behaviors between the US and other countries:

1. Number of **international agreements** from the US State Department's Treaties in Force publication
2. Existence of a **defense agreement** in the Correlates of War dataset

[17] Because factor analysis is a form of unsupervised machine learning (which is also often referred to as clustering), the factors that we feed the model will be critical to the outcome we get because it does not know the "right" answer in the way that a regression model does. It can find correlations only between the features we provide. In particular, we turned to Bayesian factor analysis to recover the underlying alignment strength from information about the kinds of behaviors that countries engage in. A Bayesian factor analysis model was most appropriate in this context because it is flexible to different kinds of data and it generates confidence intervals that speak to the precision of our estimates.

3. Level of US **diplomatic representation** abroad in Diplometrics
4. US **arms exports** abroad in SIPRI
5. Dollar amount of US **foreign aid** delivered via USAID.[18]

The model built an index that discerns how these variables relate to each other with regard to their ability to represent the concept of alignment with the US.[19]

This model did well at distinguishing between countries that the US engaged with and did not engage with, but it did not provide variation within this latter group—countries that have poor relations with the US (e.g., adversaries) as compared to those that have little engagement with the US but are not hostile.[20] As a result, we added a dimension to the model that captured the level of hostility in US relationships through these four variables:

- Number of **militarized interstate disputes** since 1945 where the US and a particular country **were on the same side**
- Number of **militarized interstate disputes** since 1945 when the US and that country **were on different sides**
- Number of **sanctions** imposed by the US on that country
- Number of **cyber-attacks** conducted against the US.[21]

We used these four variables to generate a second dimension to our measure of alignment strength so that we now captured the level of engagement between the US and other states and the level of hostility. To generate our overall alignment strength measure, we averaged these two dimensions together.[22]

[18] US State Department's Treaties in Force (https://www.state.gov/treaties-in-force/); Correlates of War (https://correlatesofwar.org/data-sets); Diplometrics (https://pardee.du.edu/diplometrics); SIPRI (https://www.sipri.org/databases); USAID (https://explorer.usaid.gov/data).

[19] Note: The study team chose to exclude economic variables such as import and export data in this model. This is because, alternatively, alignment strength results would indicate that China is among the closest three partners of the US, which does not resemble the current climate of strategic competition. While the role of economics and trade may be useful for examining particular relationships, their inclusion creates challenges to our goal of building a useful index of overall US alliance and partnership strength.

[20] This initial output is a reminder of the critical role of variable selection in model development.

[21] Ryan C. Maness, Brandon Valeriano, and Benjamin Jensen, The Dyadic Cyber Incident and Dispute Dataset Version 1.1, Aug. 1, 2017, dcid_1.1_codebook.pdf (brandonvaleriano.com).

[22] More information about our model can be found in Appendix B.

Results: What did we find?

The model output below depicts the 20 countries that are the most aligned with the US and least aligned, respectively. The model's estimates are precise enough to distinguish strong allies from weak allies and adversaries but not precise enough to identify countries' rankings.[23] Therefore, we present the results using bins to distinguish the sets of similar scores, rather than showing exact country rankings.

Top 20 countries

Our model output in Table 2 depicts the 20 countries that are the *most* aligned with the US. They are sorted into bins to provide some insight into the variation within this list.[24]

Table 2. Top 20 countries: US alignment bins

Countries	Score ranges
Canada	Scores above 4.0
Mexico	
Japan	Scores between 3.2 and 2.8
United Kingdom	
Germany	
France	Scores around 2.0
Italy	
South Korea	
Netherlands	
Philippines	Scores between 1.3 and 1.5
Panama	
Spain	
Australia	

[23] When analyzing the relative ranking of countries on this scale, an important consideration to keep in mind is that 95% confidence intervals are relatively imprecise, usually spanning about 2 points on the scale. We cannot distinguish, for example, whether Canada or Mexico in fact has the stronger relationship with the US, even if the center of Canada's confidence interval is slightly higher than Mexico's.

[24] Appendix A depicts both the scores for 2016 only (as presented in Tables 2 and 3) as well as the average scores for the 2002–2016 period for comparison (see Tables 7 and 8).

Countries	Score ranges
Colombia	
Norway	
Argentina	Scores between 1.0 and 1.2
Brazil	
Chile	
Denmark	
Peru	

Source: CNA Alliances dataset, 2021. Based on 2016 figures. Estimates can provide an approximate ranking for countries but are subject to uncertainty.

Bottom 20 countries

Conversely, our model output in Table 3 depicts the 20 countries that are the *least* aligned with the US, again sorted into substantive bins.

Table 3. Bottom 20 countries: US alignment bins

Countries	Score ranges
China	Scores below -8
Russia	Scores below -3
Iran	
North Korea	Scores below -2
Libya	Scores around -1
Syria	
Cuba	
Iraq	
Bhutan	
South Sudan	Scores around -.75
Eritrea	
Angola	
Somalia	

Countries	Score ranges
Lesotho	
Guinea-Bissau	
Namibia	
Kyrgyzstan	
Turkmenistan	
Burundi	
Cambodia	

Source: CNA Alliances dataset, 2021. Based on 2016 figures. Estimates can provide an approximate ranking for countries but are subject to uncertainty.

Implications of results: What does this mean?

There are key takeaways from these results. Above we present the results using bins to distinguish the sets of similar scores. In the tables below, we also present the results using a regional distribution to provide context for US global policy, including for defense policy as seen through combatant command (COCOM) listing.

Top 20 countries

- All countries in the top 20 list of those most closely aligned with the US are connected through a bilateral or multilateral alliance treaty: NATO, the Inter-American Treaty of Reciprocal Assistance, and the Australia, New Zealand and United States Security Treaty. Beyond this tier are a combination of other formal allies, countries that are US partners but not formal allies, and countries with more difficult bilateral relationships with the US.
- Most of the top 20 are in Europe and the Americas, as seen in Table 4.
- No African or Middle East countries are in the top 20.
- Four of the five US treaty allies in the Indo-Pacific are in the top 20.
- For US government decision-makers, important gaps are revealed when considering future US policy toward Africa, the Middle East, and the Indo-Pacific
- The top five are: Canada, Mexico, Japan, the United Kingdom (UK), and Germany.

- Two are North American neighbors. While economics and trade have been a focal point of US relationships with Canada and Mexico, our data did not consider economic factors as an area of focus.
- Three are NATO allies: Canada, the UK, and Germany.
- Canada and the UK are among the closest intelligence and defense allies of the US as Five Eyes partners. Japan is a bilateral treaty ally in Asia.

Table 4. Top 20 US alignment results: regional distribution

Americas	Europe	Indo-Pacific	Africa	Middle East
Canada	Germany	Japan	N/A	N/A
Mexico	United Kingdom	Philippines		
Panama	Netherlands	Australia		
Chile	Italy	South Korea		
Colombia	Norway			
Honduras	Turkey			
Argentina	Denmark			
Peru	France			

Source: CNA Alliances dataset, 2021. Based on 2016 figures. Regions correspond to US military geographic combatant commands.

Bottom 20 countries

- Most of the bottom 20 countries that are least aligned with the US can be found in the Indo-Pacific, Africa, and Middle East regions as seen in Table 5.
  - Most are intuitive (e.g., China, Russia, Iran, North Korea).
  - Some are counterintuitive but may be attributed to the lack of formal US diplomatic relations with the countries (e.g., Bhutan) rather than poor relations.
- Few countries in the Americas and Europe are listed in the bottom 20, suggesting strong relations or at least a relatively high degree of historical alignment across these regions.
- Nearly half of these countries are in Africa.
- Roughly half of these countries are under US sanctions, including four in Africa (Libya, South Sudan, Somalia, Burundi) and three in the Middle East (Iran, Syria, Iraq).[25]

[25] US Department of the Treasury, "Sanctions Programs and Country Information," https://home.treasury.gov/policy-issues/financial-sanctions/sanctions-programs-and-country-information.

- The results suggest more work for US policy-makers in Africa, the Middle East, and Central Asian regions if more partners are sought globally.

Table 5. Bottom 20 US alignment results: regional distribution

Americas	Europe	Indo-Pacific	Africa	Middle East/ Central Asia
Cuba	Russia	China	Libya	Iran
		North Korea	South Sudan	Syria
		Bhutan	Eritrea	Iraq
		Cambodia	Angola	Kyrgyzstan
			Somalia	Turkmenistan
			Lesotho	
			Guinea-Bissau	
			Namibia	
			Burundi	

Source: CNA Alliances dataset, 2021. Based on 2016 figures. Regions correspond to US military geographic combatant commands.

Defense implications

Upon analyzing these results and the US geographic COCOMs under which countries fall in terms of areas of responsibility (AORs), US defense planners can survey regions where allies and partners are strongest—as well as potential gaps.

Of the top 20 most aligned list, Table 6 depicts the strong presence of partners in the US European Command (EUCOM) and US Southern Command (SOUTHCOM) AORs (eight and six, respectively). Conversely, no strong US allies and partners can be found in the US Central Command (CENTCOM) and US Africa Command (AFRICOM) AORs based on the top 20 list. The regions demonstrating the weakest country alignment with Washington reside in the AFRICOM, CENTCOM, and US Indo-Pacific Command (INDOPACOM) AORs (nine, five, and four, respectively).

These results suggest more work for US policy-makers to elevate the level of close US allies and partners in Africa, the Middle East, Central Asia, and the Indo-Pacific in the years to come.

Table 6. Strongest and weakest US alignment by US military geographic combatant commands

US Combatant Command Area of Responsibility	Strength of Ties with US	
	Strongest Alignment	Weakest Alignment
EUCOM	8	1
SOUTHCOM	6	1
NORTHCOM	2	0
INDOPACOM	4	4
AFRICOM	0	9
CENTCOM	0	5

Source: CNA Alliances dataset, 2021. Top and Bottom 20 countries; based on 2016 figures.

Caveats on interpreting results: What does this not mean?

The above results provide traceable quantitative insights to help distinguish strong allies from weak allies and partners. They also help distinguish adversaries. However, there are important limits to interpreting the results.

First, these estimates are not precise enough to identify the specific rankings of individual countries because of uncertainty in the correlations identified.

Second, we acknowledge the inherently subjective nature of selecting variables for models. There is no way to verify that the correlations we measure reflect "alignment," as this is a concept that is being measured through the tabulations of sets of variables. The quality of the US alliance with Australia, for example, differs in significant ways from that with Panama, for example, though the two measures of alignment strength are similar. The study team selected nine variables that indicated behaviors that are suggestive of alliances and strategic partnerships. As we discussed earlier with this study's focus on the security dimension of IR, the model leaves out other important aspects of IR, such as commercial and financial ties. Its results reflect those decisions.

Third, this method makes the assumption that previous correlations among variables continue to the present, or in other words the general environment remains similar. Yet, the potential for significant change always exists. Therefore, the model's results should be interpreted in this context.

Even taking into account these results and their caveats, we have developed an intuitive measure of alignment strength through access to nine pieces of information and without requiring information about trade flows, geography, or cultural background.

Findings: Predicting US Alliances and Partnerships

The idea that inspired this project—and its most ambitious aim—is the prospect of predicting future US alliances and partnerships. Our third research question is: "Can we predict which alliances and partnerships will be advantageous for US policy-makers to pursue?" This section lays out our analytical process, our findings, the implications of these findings, and the caveats on interpreting our findings.

Analytical process: What did we do?

Drawing on the years of data compiled, we wanted to see if we could turn back the clock and test the model by using it to predict alignment strength within a 10-year period (between 2004 and 2014).[26] In this way, we could test our model's ability to generate useful analyses about future events by applying it to a past period of analysis where inputs and outcomes are both known.

- Built and employed a supervised machine-learning model to forecast alignment score.
- Method: Elastic Net regression
- Tool: R software

Using data science methods, the study team approached the third research question by building a supervised machine-learning model. While the unsupervised model used in the previous section sought to uncover unknown groupings between countries based on their similarities, the supervised model used in this section knew the "right" answer (i.e., which countries were estimated to be strong US allies and which were not). Its task was to find the best set of economic, political, and demographic

[26] To predict alignment strength for the years between 2004 and 2014, we used data starting in 2002 and running up to the year under analysis. Specifically, the training data was all data from 2002 to $Year_{x-1}$, while the test data was all data for $Year_x$. Thus, to test for 2004, the model trained on data from 2002 and 2003; for testing 2005, it trained on data from 2002 to 2004, etc.

characteristics that predicted alignment strength. In particular, we turned to Elastic Net regression to identify these predictive factors.[27]

This process involved selecting one of our identified variables that signifies alignment with the US and determining how well this single variable can be forecasted using Elastic Net regression. This supervised model used the alignment index created for the first research question as the target variable for developing predictions.[28]

Results: What did we find?

Our first finding is that *predicted* alignment strength (produced by the model) correlates with alignment strength that was calculated previously as the metric for developing predictions.[29] Our plot in Figure 3 shows the predicted score along the x-axis against the actual score on the y-axis. Observations directly on the black line mean that the model exactly predicted the next year's alliance score using only information about the current year. Multiple predictions over time for the same country are shown in the same color, with more transparent points indicating older observations and more opaque points indicating more recent observations. In general, the observations cluster around the black line, which means that the predictions are relatively close to the actual value.[30]

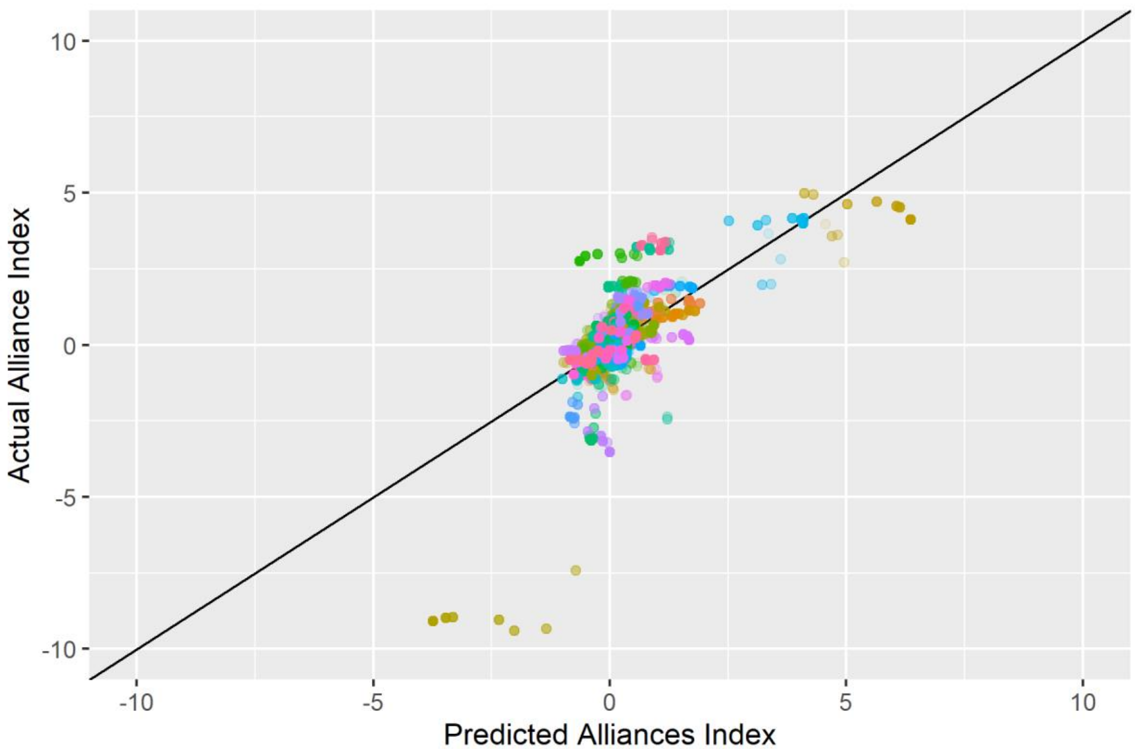
[27] Elastic Net regression is a generalization of ordinary least squares (OLS) linear regression which penalizes the model for finding strong correlations or using many variables. This penalization means that the correlations it finds need to have strong predictive influence. This property reduces OLS's tendency to overfit to the training data, leading to poor performance on testing data. CNA used the standard glmnet library in R which was written by Trevor Hastie, one of the inventors of the method. The paper gives an example of applying the method to identifying genes that predict the risk for leukemia (https://web.stanford.edu/~hastie/Papers/B67.2%20(2005)%20301-320%20Zou%20&%20Hastie.pdf, page 313).

[28] More information about our model can be found in Appendix C.

[29] The correlation between the prediction and calculated alignment strength is .70.

[30] In fact, if we calculate the average distance from the predicted values to the average values, we find that the model's estimated alliance score is usually within half a scale point of the actual alignment strength measure, or about half a standard deviation of the alliance score.

Figure 3. Predicting US alliances and partnerships[31]

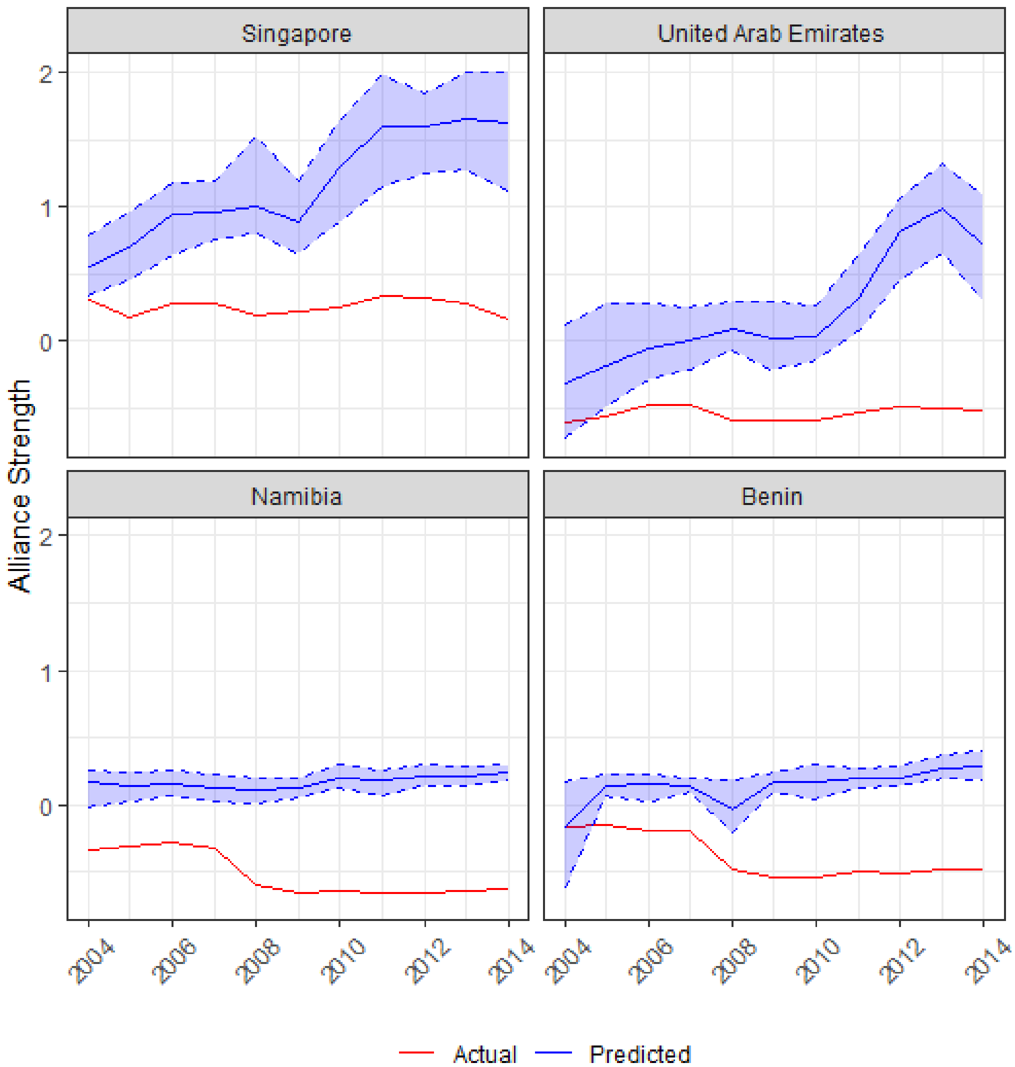


Source: CNA Alliances dataset, 2021. Based on 2004–2014 predicted alignment scores.

Our second finding is that US alignment strength with some countries (calculated in the first research question) is *lower than their predicted alignment.* Singapore, United Arab Emirates, Namibia, Benin, and Lesotho all fell into this category. Figure 4 shows the predicted score in blue; the shading shows the 95 percent confidence interval of the prediction. The lines in red show the alignment scores calculated in the first research question. In each of these countries, the predicted alliance score for 2014 was about one index point higher than was actually measured that year.

[31] Each colored dot represents the estimated alliance strength for a particular country in a given year. The opacity of the dot indicates which year the estimate is for, with lighter dots indicating earlier years and darker dots indicating later years. Dots near the central line indicate that the actual and predicted alliance strengths were very similar, while dots further from the central line indicate divergence between the actual and predicted strengths.

Figure 4. US alignment strength: lower than predicted



Source: CNA Alliances dataset, 2021. Based on 2004–2014 predicted alignment scores.

Implications of results: What does this mean?

The first takeaway from this set of results is that we can forecast the likely strength of US alliances and partnerships, with confidence for up to five years into the future.[32] We can make this claim on the basis of taking data from an earlier, known time period, analyzing how it correlates with factors today to identify model parameters, and then developing a prediction for a future date based on contemporary data. To evaluate this claim, we made a "prediction" that relied exclusively on historical data (in the 2004–2014 period). As a result of these methods, US government policy-makers can use this model to evaluate perceptions that particular alliances are improving.

Second, policy-makers can evaluate how the alignment forecasts of particular countries compare with others in the region. For example, the United Arab Emirates is lower in US alignment than predicted; how does this compare with forecasts of other Gulf states?

Third, these findings raise important issues for policy-makers to consider. Countries such as Singapore and the United Arab Emirates provide important military access for the US. For example, Singapore permits rotations of US littoral combat ships and P-8 Poseidon aircraft. Yet, Washington's relationships with these countries confront challenges in other dimensions of their ties, such as this news headline: "F-35 Sale to U.A.E. Imperiled over US Concerns about Ties to China."[33] That their alignment scores are lower than predicted may invite further examination of these critical relationships.

Caveats on interpreting results: What does this not mean?

Our results provide a replicable method of forecasting US alliances and partnerships between one and five years into the future. However, important caveats remain when interpreting the results.

- First, the forecast relies upon an assumption that variables outside the model, and the general structure of the international environment, are roughly constant. In this case, we assumed that the future period in question (2014) bears structural similarities to the period under examination (2004). In other words, there are some 10-year periods

[32] Figures 3 and 4 depict the results of predicting alignment scores for the next year, but we found similarly accurate results for up to five years into the future. Specifically, our test data was again all data for $Year_x$ (starting in 2009), but the training data was all data from 2002 to $Year_{x-5}$.

[33] Warren P. Strobel and Nancy A. Youssef, "F-35 Sale to U.A.E. Imperiled over US Concerns about Ties to China," *Wall Street Journal*, May 25, 2021.

that could see more rapid changes in US alignment than others, including changes to states' behaviors and preferences more broadly, which would affect the success of this pattern-based prediction.

- Second, we are limiting our forecast to at most a five-year period. Predictive analytics loses accuracy the farther out the timespan. We found the error rate is the same whether predicting one or five years into the future. For policy-makers thinking 10 years into the future (early 2030s) and contemplating the possibility of major shifts to the world order (e.g., a US-China conflict, impediments to global economic integration), our forecast is less useful.
- Third, the model's estimates are not precise enough to identify the specific rankings of individual countries. Instead, the model can indicate whether a country is likely to be a strong ally, neutral, or a strong adversary.

Conclusion

Our project began with an ambitious goal, but also with a healthy dose of skepticism about the power to predict the future state of US alliances and partnerships. The prospect of prediction in social science research has long been controversial,[34] especially because of its relative lack of success when compared to the physical sciences. Meanwhile, the topic of Washington's international relationships has become more salient in the era of GPC. Policy-makers require robust and innovative analytical methods to study complex issues in the coming years.

After building a dataset, creating machine-learning models, and analyzing the results, we conclude that data science can provide a new source of insight into the study of alliances. Broadly, it can help policy-makers develop tools that may be useful on a variety of issues related to the management of US alliances and partnerships, such as military basing and security cooperation. At the same time, experts should keep in mind the limitations of this and other methods when interpreting results and applying these insights to policy. As described earlier, some of these caveats involve acknowledging the subjective nature of variable selection when developing models and making explicit that forecasts rely upon an assumption about international relationships observed during a specified time period—in the present era or historically—continuing into the future.

Keeping these caveats in mind, the study team found:

- We can develop quantitative estimates of current alignment strength that incorporate multiple aspects of international alignments by using Bayesian factor analysis.
- We can provide reasonable predictions of alignment strength that inform our understanding of how alliances are on track to progress in the coming five years and which alliances are weaker than would be expected.

Having this additional understanding of the current state of US alliances and partnerships, and how they might evolve, can empower policy-makers. For example, they may be able to detect when strategically important relationships are performing at lower levels than expected—as found in our model—and take measures to bolster these alliances and partnerships. Being able to track these relationships may also enable officials to make more informed decisions about allocating scarce resources to strategic partnerships.

This has been an exploratory project, with much of our effort taken to investigate the basic question of whether data science could offer insight into the study of alliances and

[34] Philip E. Tetlock, *Expert Political Judgment: How Good Is It? How Can We Know?* Princeton: Princeton University Press, 2005.

partnerships. Now that we have concluded that it does, the next step is for analysts and policy-makers to dig deeper into this approach and the dataset to examine its potential utility for US relationships. One area that this research suggests is a closer analysis of country traits and characteristics and their potential effects on US alliances and partnerships. For example, if a particular country falls in its rankings on indicators of civil liberties (e.g., Freedom House report), what type of relationship could US policy-makers expect to see and how would this relationship compare with other regional countries? Another avenue is to expand our survey of available datasets with additional types of variables to provide greater nuance to our analysis. Through machine learning, policy-makers can gain more precision in their efforts to navigate the complex web of US alliances and partnerships in an era of strategic competition.

Appendix A: Expanded Q1 Output

Table 7. Top 20 countries: 2016 and 2002–2016 averaged

	2002–2016 Averaged	2016 Only	
Countries	**Score ranges**	**Countries**	**Score ranges**
Canada	Between 4.2 and 3.6	Canada	Above 4.0
Mexico		Mexico	
Germany	Between 2.4 and 2.1	Japan	Between 3.2 and 2.8
United Kingdom		United Kingdom	
Japan		Germany	
Netherlands	Between 1.8 and 1.6	France	Around 2.0
Philippines		Italy	
Panama		South Korea	
Italy	Between 1.3 and 1.1	Netherlands	
Chile		Philippines	Between 1.5 and 1.3
Australia		Panama	
Norway		Spain	
Turkey	Between 1.1 and 1.0	Australia	
Denmark		Colombia	
Colombia		Norway	
France		Argentina	Between 1.2 and 1.0
Honduras		Brazil	
Argentina	Below 1.0	Chile	
South Korea		Denmark	
Peru		Peru	

Source: CNA Alliances dataset, 2021. Estimates can provide an approximate ranking for countries but are subject to uncertainty.

Table 8. Bottom 20 countries: 2016 and 2002–2016 averaged

	2002–2016 Averaged	2016 Only	
Countries	**Score ranges**	**Countries**	**Score ranges**
China	Below -5.5	China	Below -8
Iran	Around -2	Russia	Below -3
North Korea		Iran	
Russia		North Korea	Below -2
Libya	Around -1	Libya	Around -1
Iraq		Syria	
Syria		Cuba	
Cuba		Iraq	
South Sudan	Around -.75 or higher	Bhutan	
Cambodia		South Sudan	Around -.75
Kosovo		Eritrea	
Vietnam		Angola	
Algeria		Somalia	
Bhutan		Lesotho	
Laos		Guinea-Bissau	
Sudan		Namibia	
Taiwan		Kyrgyzstan	
Myanmar		Turkmenistan	
Eritrea		Burundi	
Zimbabwe		Cambodia	

Source: CNA Alliances dataset, 2021. Estimates can provide an approximate ranking for countries but are subject to uncertainty.

Appendix B: Unsupervised Machine-Learning Model in Detail

The study of alliances and partnerships is becoming more robust and increasing in salience in the era of strategic competition. Research has advanced beyond examining formal commitments of defense to consider other measures of international alignment, such as similarity in voting in the United Nations General Assembly,[35] shared membership in international organizations,[36] trade flows,[37] and arms sales.[38]

Once multiple measures are considered, however, it becomes difficult to determine the overall strength of an alliance. How, for example, should researchers weigh a trade dispute against a million dollars of foreign aid or a shared UN vote? In cases like these, we can devise scales that average several indices, often placing more weight on some factors than others, but combining multiple measures is usually not done in any principled manner.

Method

Statistical methods for uncovering "latent variables" offer a way to combine multiple measures of alignment strength in a traceable manner. A latent variable is an underlying construct that influences observable behavior but cannot itself be directly observed. For example, latent variables appear commonly in work on ideology, where preferences over specific policies are related to an underlying liberal-conservative ideology that is itself unmeasurable other than through its effects on policy preferences.[39] While many factors may contribute to an individual's support for a specific policy, the individual's underlying ideology is an important contributor. By measuring how a set of behaviors move together, statistical methods can

[35] E. Voeten, 2013. Data and analyses of voting in the United Nations General Assembly (pp. 54-66). London: Routledge.

[36] Christina L. Davis and Meredith Wilf, "Joining the Club: Accession to the GATT/WTO." *The Journal of Politics* 79, no. 3 (2017): 964-978.

[37] Brian M. Pollins, "Conflict, cooperation, and commerce: The effect of international political interactions on bilateral trade flows." *American Journal of Political Science* (1989): 737-761.

[38] James Fearon and Bertel Hansen, "The arms trade, international alignment, and international conflict." Stanford University International Relations Workshop, 2017, https://politicalscience.stanford.edu/events/international-relations-workshop/james-fearon-arms-trade-international-alignments-and

[39] Conover and Feldman. 1981. The origins and meaning of liberal/conservative self-identifications. *American Journal of Political Science* 25 (November): 617.

uncover the underlying latent concept driving the behaviors together. While we use these models to uncover a single factor, the same techniques can be used to derive multiple underlying factors, such as differentiating between social and economic policy preferences. Deciding how many factors to generate is at the discretion of the researcher, and heuristics exist to evaluate the optimal number of factors to explain any observed data.

In the application to alliances, the key intuition is that the strength of an alliance is also a latent variable that cannot be measured directly, although its effects on behavior, such as signing defense agreement or providing international aid, can be observed. Taking this perspective allows us to scale the factors we believe contribute to alignment strength in a principled manner while imposing minimal assumptions. The model assumes only that there is an underlying latent scale and that each of the factors identified by the researcher contributes in some way to that scale, even if that way is zero or nearly zero. The model then identifies the relationships between the latent scale and these factors, also known as the factor loadings, which are most consistent with the observed data. Exactly how these factor loadings are determined depends on the specific method, but the concepts are largely the same.

For this project, we measured the latent strength of alliances using a Bayesian factor analysis model,[40] a generalization that combines aspects of the exploratory factor analysis model,[41] which assumes that all data are continuous, and the item response theory model,[42] which assumes that all data are ordinal. The Bayesian factor analysis model incorporates both kinds of data simultaneously and includes both the exploratory factor analysis model and the item response theory model as special cases when the data are either all continuous or all ordinal. Beyond its flexibility in using multiple types of data, the Bayesian factor analysis model is preferable to the exploratory factor analysis model because it can represent the uncertainty behind its estimates. These features have made Bayesian factor analysis attractive in the field of IR, and scholars have used similar methods to study whether the power of the signatories or the terms of the agreement determine the strength of an alliance agreement.[43]

For these models to produce an accurate measure, we must ensure that the observable features we provide the model are actually related to the underlying concept we are trying to measure. This is intuitive; the model has no access to the ground truth other than through the data we provide it, and it cannot read our minds. If we intend to measure alignment strength but give

[40] Kevin M. Quinn. “Bayesian factor analysis for mixed ordinal and continuous responses.” *Political Analysis* 12, no. 4 (2004): 338-353.

[41] Leandre R. Fabrigar and Duane T. Wegener. *Exploratory Factor Analysis*. Oxford University Press, 2011.

[42] Wim J. van der Linden and Ronald K. Hambleton, eds. *Handbook of Modern Item Response Theory*. Springer Science & Business Media, 2013.

[43] Brett V. Benson and Joshua D. Clinton. “Assessing the variation of formal military alliances.” *Journal of Conflict Resolution* 60, no. 5 (2016): 866-898.

the model features that are unrelated, it will still estimate a latent scale that ties those features together, but this scale will have nothing to do with alliances. It is important to remember the label that we attach to the results is our own concept, i.e., a shorthand that we use for saying, "the latent scale that accounts for the common variance between the observed values of A, B, C, and D given our scoping conditions and other measurement considerations." To frame the same point slightly differently; factor analysis models cannot be used as hypotheses tests to determine whether the factors provided are correlated with a latent concept. Rather, the model assumes that the factors are correlated and it finds the best combination of weights. To test whether a factor is correlated with some index would require access to an independent measure of that index.

Data

We relied on nine variables to recover these two dimensions (engagement and hostility) of alignment strength. We selected these variables because they each represent a unique facet of alliance behavior spanning economic, political, and military implications. The number of variables to include is at the discretion of the researcher, but using a more limited set of variables produced indices that matched more closely our substantive understanding of alignment strength. Because we had strong prior beliefs about which dimension each of these variables should relate to, we restricted the model to using only a preselected set of predictors for each dimension.[44] We did this to keep the two dimensions conceptually distinct and to avoid the interdependence between engagement and hostility. A list of which variables we selected for each dimension is provided below.

Variables related to engagement:

1. Defense agreements: whether the country had a defense agreement with the US in the specified year. Data on defense agreements come from the Correlates of War Formal Interstate Alliances Database (v4).
2. Arms sales: the trade in value of US arms exports to the country in the given year. Data on arms sales come from the SIPRI Arms Transfer Database.
3. Foreign aid: the recorded value of USAID foreign aid to the country in the given year. Interestingly, this value can be negative. Data on foreign aid come from the US State Department Foreign Aid Explorer.

[44] For the Bayesian model, this is the equivalent of setting the prior to exactly 0 for each of the variables we did not select.

4. Diplomatic representation: the level of US diplomatic representation in the country in a given year. The data capture five levels of diplomatic representation spanning from "interests served by" to "ambassador." Data on diplomatic representation come from the Diplometrics database maintained by the Pardee Center for International Futures.
5. Agreement count: the number of international agreements in force between the country and the US in a given year. Data on international agreements come from the US State Department's Treaties in Force list.

Variables related to hostility:

1. Dispute allies: Cumulative count of all militarized interstate disputes (MIDs) where the US and the country are on the same side since 1945. Data on MIDS come from the Correlates of War Militarized Interstate Disputes v 5.0 database.
2. Dispute adversaries: Cumulative count of all MIDs where the US and the country are on the opposite side since 1945. Data on MIDS come from the Correlates of War Militarized Interstate Disputes v 5.0 database.
3. Economic sanctions: Cumulative count of sanctions imposed from the US on the target country since 1945. Data on sanctions are from the Threat and Imposition of Sanctions (TIES) database.
4. Cyber attacks: Cumulative count of cyber attacks against the US believed to have been conducted by the target country. Data on cyber attacks come from the Cyber Security Incident Data.

We use the cumulative sum of incidents since 1945 for our measure of hostility instead of the current year's value because active hostilities are relatively rare but likely to have long-lasting implications and reflect long-standing disagreements. Doing so ensures that, for example, the relationship between the US and Iraq in the year after the Gulf War (no conflict this year but conflict prior) is observationally distinct from the relationship between the US and the United Kingdom. Starting our counts since 1945 ensures that they reflect the international realignment following World War II and that enough data are available to capture long-standing hostilities even if conflict breaks out only infrequently.

Using these nine variables, we recovered two latent dimensions of underlying alignment strength between 148 countries and the US from 1992 until 2016. We selected 1992 as the starting point for our analysis because it coincides with the end of the Cold War and the realignment of international politics. We used 2016 as our end date because several important sources of data are not available after that point. We also excluded a number of states with populations less than 1 million in 1992, as small states were less likely to have the necessary data available.

For inclusion in our model, each of the continuous variables (arms sales, foreign aid, diplomatic representation, agreement count, dispute allies, dispute adversaries, economic sanctions, and cyber attacks) was standardized to have mean 0 and standard deviation 1. This transformation allows us to interpret their coefficients in the latent variable model as factor loadings. We estimated our model using the open -source *MCMCpack* library in R and ran separate models for each year of our study. By separating each year, we allow the ways in which alliances manifest themselves over time to vary freely. The alternative is to use a dynamic factor analysis model that explicitly models temporal dependence,[45] which uses cross-temporal information to generate more precise estimates. However, we chose our separated model for its minimal assumptions and ease of interpretation.

[45] Kevin Reuning, Michael R. Kenwick, and Christopher J. Fariss, "Exploring the dynamics of latent variable models." *Political Analysis* 27, no. 4 (2019): 503-517.

Appendix C: Supervised Machine-Learning Model in Detail

Policy-makers are interested not only in the strength of alliances today but also their strength tomorrow. We can generate these predictions of alignment strength tomorrow by identifying the factors that tend to correlate with stronger and weaker alliances. They include the kinds of political regimes or economic structures that predominate in the countries with which the US tends to have strong relationships. While such correlations do not necessarily imply causal relationships (e.g., that democratic governments cause stronger alliances with the US rather than the other way around), understanding these correlations would still provide policy-makers with guidance on how to manage and maintain such alliances.

Identifying causal relationships (i.e., which factors cause the US to have better or worse relationships with particular countries) is much more challenging. Broadly speaking, no methods exist that allow analysts to test whether a large number of possible factors cause alliances to become stronger or weaker. The underlying difficulty is finding conditions that approximate a laboratory experiment, i.e., hold everything else equal while varying the key factors under consideration. Sometimes these factors can be approximated through natural experiments, i.e., a sudden change in regime type brought on by the death of a political leader, but such conditions are by their nature rare and even then are unlikely to be entirely unrelated to other factors, such as economic conditions, that might themselves influence the strength of an alliance. Moreover, studying how various policy instruments affect the strength of alliances is complicated by the strategic incentives of the actors involved.

Method

Many of the familiar tools for quantitative social science, such as linear regression, are designed to undercover causal relationships given that a large number of assumptions hold true. These assumptions, such as the lack of unobserved factors that correlate with both the independent variables under consideration (i.e., political regime) and the dependent variable (i.e., alignment strength), are unlikely to hold in this case. Because this causal interpretation is not possible, we can make further adjustments to these models that improve their predictive performance at the cost of causal interpretation. In particular, a data science method known as "regularization" is particularly effective in narrowing down large sets of predictive variables to identify a handful with the most predictive power. This narrowing down process does not only make interpreting the model results easier, but also leads often to better predictive performance because it weeds out some of the idiosyncratic associations that appear in the underlying data and focuses on the overarching persistent trends.

A traditional statistical model identifies how input variables are related to output variables by finding the set of coefficients for these inputs that best predicts the output variable. The model iteratively checks a large number of possible coefficients and chooses the set of coefficients that has the smallest error.[46] Regularization applies this same process, but penalizes the model for including many large coefficients and thus guides it towards choosing smaller coefficients. This yields a set of coefficients that generates slightly higher errors on the training, but these coefficients usually perform better on new data that were not used to generate the model. There is no a priori way to determine how large this complexity penalty should be, so the usual approach is to test a large range of complexity penalties and choose the penalty that generates the best performance.

The two main ways to implement regularization in a regression context are LASSO and Ridge regression. Both take a standard linear regression model and add this complexity penalty. The two models differ in exactly how that penalty is chosen; LASSO uses the absolute value of the sum of the coefficients used by the model, while Ridge takes the sum of the squared coefficients used by the model. These different calculations make some difference for the coefficients chosen by the model; LASSO sets more coefficients to exactly zero and is better for pulling out a single variable out of a set of related variables; while Ridge is better when several variables are all important but interrelated. Rather than choosing one or other of these methods, we employ a third method known as Elastic Net, which applies both penalties at the same time, splitting the weight between them. For convenience, we set this weight to apply the LASSO and Ridge penalties equally.

In contrast to the unsupervised method used to measure alignment strength, we use a supervised method to predict alignment strength. We did so because we have a set of data with the outcome that we are interested in (i.e., alignment strength) and want to determine the associations between a number of independent variables (e.g., political regime) and that outcome. This is different than the goal of unsupervised learning where we had only a set of independent variables and wanted to understand how they related to each other.

[46] For some model types, such as ordinary least squares, we can identify these best coefficients with the least error analytically without actually computing the error for different sets of coefficients, but the process of iteratively checking coefficients would yield the same answer as the analytic solutions.

Data

For this section, we are interested in predicting the overall alignment strength scores generated by the Bayesian factor analysis model. As a reminder, that overall alignment strength score was generated by combining two aspects of alliance behavior—engagement and hostility—into a single index. If either of these dimensions was particularly important to the analytic effort at hand, the predictive model could also be used to forecast either engagement or hostility independently. Because the goal is to predict alignment strength in the future, rather than now, we look at the alliance score one year in the future from when the predictive variables were recorded. This allows us to approximate better the information that would be available to policy-makers when making decisions about resource allocation.

We predict this overall alignment strength score using a set of 17 predictive variables that were not used in computing those scores themselves. We choose a set of variables that we believed would capture the political and economic factors likely to contribute to and/or reflect the strength of the alliances between the US and foreign countries. These include several variables capturing the flow of imports and exports, several related to regime type and civil liberties, and several related to the country's basic demographics, such as its GDP per capita and its total population. Below are our independent variables:

1. usexports – COW Trade 4.0: US exports to country X in year Y
2. usimports – COW Trade 4.0: US imports from country X in year Y
3. exportspike – COW Trade 4.0: Captures whether US exports to country Y rose by more than 50 percent year-on-year
4. importspike – COW Trade 4.0: Captures whether US imports from country Y rose by more than 50 percent year-on-year
5. exportdip – COW Trade 4.0: Captures whether US exports to country Y fell by more than 50 percent year-on-year
6. importdip – COW Trade 4.0: Captures whether US imports from country Y fell by more than 50 percent year-on-year
7. totaltrade – COW Trade 4.0: Sum of exports and imports with country X in year Y
8. v2x_regime – v_dem - How can the political regime overall be classified considering the competitiveness of access to power (polyarchy) as well as liberal principles?
9. v2x_civlib – v_dem - Question: To what extent is civil liberty respected?
10. v2x_corr – v_dem - Question: How pervasive is political corruption?
11. v2x_gender – v_dem - Question: How politically empowered are women?

12. v2x_rule – v_dem - Question: To what extent are laws transparently, independently, predictably, impartially, and equally enforced, and to what extent do the actions of government officials comply with the law?
13. e_p_polity – Polity Score from Polity IV dataset
14. e_regiongeo – Geographic region as recorded by the UN Statistics Division
15. e_migdppc – GDP per capita from Maddison Project Database
16. e_wb_pop – Population figures
17. e_fh_status – Freedom House (2018) Status scores

Using these 17 variables, we generated predictions of the following year's alignment strength from 2004 through 2014. For each year, we train the model on the relationship between the current year's value of the predictive variables and the next year's value of the dependent variable. This lagged relationship reflects how policy-makers would use current conditions to forecast future relationship status. When estimating these relationships, we use all prior years of data, meaning that relationships estimated on later years have access to more prior years of data than the early years in the model. The earliest year for which we generated predictive values (2004) has access to data from 2002 and 2003, before which we did not generate alliance scores. The last year for which we estimated the relationship with future alignment strength is 2014 because missing data on key independent variables prevented our Bayesian factor analysis model from generating scores after 2015. As with the Bayesian factor analysis model, we include only countries with populations greater than 1 million in 1992 as smaller states were less likely to have the necessary data available.

Figures

Tables

Abbreviations

AFRICOM	US Africa Command
AOR	area of responsibility
CENTCOM	US Central Command
COCOM	combatant command
DOD	Department of Defense
EUCOM	US European Command
GDAP	Guidance for Development of Alliances and Partnerships
GPC	great power competition
INDOPACOM	US Indo-Pacific Command
IR	International Relations
NATO	North Atlantic Treaty Organization
NDS	National Defense Strategy
NMS	National Military Strategy
NSS	National Security Strategy
SIPRI	Stockholm International Peace Research Institute
SOUTHCOM	US Southern Command
USAID	US Agency for International Development
UK	United Kingdom

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SP3 provides strategic and political-military analysis informed by regional expertise to support operational and policy-level decision-makers across the Department of the Navy, the Office of the Secretary of Defense, the unified combatant commands, the intelligence community, and domestic agencies. The division leverages social science research methods, field research, regional expertise, primary language skills, Track 1.5 partnerships, and policy and operational experience to support senior decision-makers.

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