
INTRODUCING ICBe: VERY HIGH RECALL AND PRECISION EVENT EXTRACTION FROM NARRATIVES ABOUT INTERNATIONAL CRISES

A PREPRINT

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Abstract

How do international crises unfold? We conceptualize of international relations as a strategic chess game between adversaries and develop a systematic way to measure pieces, moves, and gambits accurately and consistently over a hundred years of history. We introduce a new ontology and dataset of international events called ICBe based on a very high-quality corpus of narratives from the International Crisis Behavior (ICB) Project. We demonstrate that ICBe has higher coverage, recall, and precision than existing state of the art datasets and conduct two detailed case studies of the Cuban Missile Crisis (1962) and Crimea-Donbas Crisis (2014). We further introduce two new event visualizations (event iconography and crisis maps), an automated benchmark for measuring event recall using natural language processing (synthetic narratives), and an ontology reconstruction task for objectively measuring event precision. We make the data, online appendix, replication material, and visualizations of every historical episode available at a companion website www.crisisevents.org and the github repository.

Keywords Diplomacy · War · Crises · International Affairs · Computational Social Science

Significance Statement

Countries routinely face crises that risk escalating into full scale war but we do not have systematic measurements of the progression of past crises and what moves and counter moves led to or helped avoid war. Instead policy makers typically rely on one or two historical analogies, chosen through ad hoc selection criteria, and described in unsystematic terms. This paper introduces a new scientific approach to measuring the step by step moves of international crises over the last hundred years, combining subject expertise with state of the art natural language processing and machine learning methods. It serves as a guide for constructing and evaluating large scale measurement collection in the social sciences.

If we could record every important interaction between countries in all of diplomacy, military conflict, and international political economy, how much unique information would this chronicle amount to, and how surprised would we be to see something new? In other words, what is the entropy of international relations? This record could in principle be unbounded, but the central conceit of social science is that there are structural regularities that limit what actors can do, their best options, and even which actors are likely to survive (1, 2). If so, then these events can be systematically measured, and accordingly, massive effort is expended in social science attempting to record these regularities.¹ Thanks to improvements in natural language processing, more open-ended efforts have begun to capture entire unstructured streams of events from international news reports.² How close these efforts are to accurately measuring all or even most of what is essential in international relations is an open empirical question, one for which we provide new evidence here.

Our contribution is a high coverage ontology and event dataset for key historical episodes in 20th and 21st-century international relations. We develop a large, flexible ontology of international events with the help of both human coders and natural language processing. We apply it sentence-by-sentence to an unusually high-quality corpus of historical narratives of international crises (1, 29–32). The result is a new lower bound estimate of how much actually happens between states during pivotal historical episodes. We then develop several methods for objectively gauging

how well these event codings reconstruct the information contained in the original narrative. We conclude by benchmarking our event codings against several current state-of-the-art event data collection efforts. We find that existing systems produce sequences of events that do not contain enough information to reconstruct the underlying historical episode. The underlying fine-grained variation in international affairs is unrecognizable through the lens of current quantification efforts.

This is a measurement paper that makes the following argument — there is a real-world unobserved latent concept known as international relations, we propose a method for systematically measuring it, we successfully apply this method producing a new large scale set of measurements, those measurements exhibit several desirable kinds of internal and external validity, and those measurements out-perform other existing approaches. The article organizes that argument into eight sections: task definition; corpus; priors/existing state of the art; ICBe coding process; internal consistency; case study selection; recall; and precision. A final section concludes.

Task Definition

We consider the measurement task of abstracting discrete events about a historical episode in international relations. The easiest way to convey the task is with an example. Figure 1 shows a narrative account of the Cuban Missile Crisis (1962) alongside a mapping from each natural language sentence to discrete machine readable abstractive events. Formally, a historical episode, H , is demarcated by a period of time $[T_{start}, T_{end}] \in T$, a set of Players $p \in P$, and a set of behaviors they undertook during that time $b \in B$. International Relations, IR , is the system of regularities that govern the strategic interactions that world actors make during a historical episode, given their available options, preferences, beliefs, and expectations of choices made by others. We observe neither H nor IR directly. Rather the Historical Record, HR , produces documents $d \in D$ containing some relevant and true (as well as irrelevant and untrue) information about behaviors that were undertaken recorded in the form of unstructured natural language text. The task is to combine informative priors about IR with an unstructured corpus D to produce a series of structured discrete events, $e \in E$, that have high coverage, precision, and recall over what actually took place in history, H .

¹See work on crises (3, 4), militarized disputes (5–7), wars (8, 9), organized violence (10, 11), political violence (12), sanctions (13), trade (14), and international agreements (15–17), dispute resolution (17, 18), and diplomacy (19, 20).

²See (21); (22); (23); (24); (25); (26). On event-extraction from images and social-media see (27) and (28).

Figure 1: Case Study 1: Cuban Missile Crisis (1962) - ICB Narrative vs. ICBe Events

Corpus

For our corpus, D , we select a set of unusually high-quality historical narratives from the International Crisis Behavior (ICB) project ($n = 471$) (SI Appendix, Table A1)(33, 34).³ Their domain is 20th and 21st-century crises, defined as a change in the type, or an increase in the intensity, of disruptive interaction with a heightened probability of military hostilities that destabilizes states' relationships or challenges the structure of the international system (3).⁴ Crises are a significant focus of detailed single case studies and case comparisons because they provide an opportunity to examine behaviors in IR short of, or at least prior to, full conflict (3, 35–42). Case selection was exhaustive based on a survey of world news archives and region experts, cross-checked against other databases of war and conflict, and non-English sources (33, 43). Each narrative was written by consensus by a small number of scholars, using a uniform coding scheme, with similar specificity (44). The corpus is unique in IR because it is designed to be used in a downstream quantitative coding project.

Prior Beliefs about IR, Ontological Coverage, and the Existing State of the Art

Next we draw informative prior beliefs about the underlying process of IR that we expect to govern behavior during historical episodes and their conversion to the historical record. We organize our prior beliefs along two overarching axes, summarized in detail by Table 1.

The first axis (rows) represents the types of information we expect to find in IR and forms the basis for our proposed ontology. We employ a metaphor of a chess game, with players (polities, rebel groups, IGOs, etc.), pieces (military platforms, civilians, domains), and behaviors (think, say, do). Precise sequencing is required to capture gambits (sequences of moves) and outcomes (victory, defeat, peace, etc.), while precise geo-coding is required to understand the chessboard (medium of conflict). We find 472 actors and 117 different behaviors, and provide a full codebook in the online material.⁵

We base our informed priors primarily on two sources of information. The first is the extensive existing measurement efforts of IR which we provide citations to alongside each concept. Second, we performed preliminary natural language processing of the corpus and identified named entities and behaviors mentioned in the text. Verbs were matched to the most likely

³The Online Appendix is at the ICBEEventData Github Repository.

⁴On near crises see (32).

⁵See the Github Repository ICBEEventData.

definition found in Wordnet (45), tallied, and then aggregated into a smaller number hypernyms balancing conceptual detail and manageable sparsity for human coding (SI Appendix, Table A2).

The second axis (columns) compares the very high ontological coverage of ICBe to existing state of the art systems in production and with global coverage. They begin with our contribution ICBe, alongside other event-level datasets including CAMEO dictionary lookup based systems (Historical Phoenix (46); ICEWS (24, 25); Terrier (26)), the Militarized Interstate Disputes Incidents dataset, and the UCDP-GED dataset (10, 11, 47).⁶ The final set of columns compares episode-level datasets beginning with the original ICB project (3, 4, 56); the Militarized Interstate Disputes dataset (5, 6, 57, 58), and the Correlates of War (8). With the exception of large scale CAMEO dictionary based systems, the existing state of the art quantitative datasets ignore the vast majority of the information content found in international relations.⁷

ICBe Coding Process

The ICBe ontology follows a hierarchical design philosophy where a smaller number of significant decisions are made early on and then progressively refined into more specific details (59).⁸ Each coder was instructed to first thoroughly read the full crisis narrative and then presented with a custom graphical user interface (SI Appendix, Fig. B1). Coders then proceeded sentence by sentence, choosing the number of events (0-3) that occurred, the highest behavior (thought, speech, or activity), a set of players (P), whether the means were primarily armed or unarmed, whether there was an increase or decrease in aggression (uncooperative/escalating or cooperative/de-escalating), and finally one or more non-mutually exclusive specific activities. Some additional details like location and timing information was always collected while other details were only collected if appropriate, e.g. force size, fatalities, domains, units, etc. A unique feature of the ontology is that thought, speech, and do behaviors can be nested into combinations, e.g. an offer for the U.S.S.R. to remove missiles from Cuba in exchange for the U.S. removing missiles from Turkey. Through

⁶Additional relevant but dated or too small of an overlap in domain include BCOW (48), WEIS (49), CREON (50), CASCON (51), SHERFACS (52), Real-Time Phoenix (23), and COFEE (53) (see histories in (54) and (55)).

⁷See (53) for a recent review of ontological depth and availability of Gold Standard example text.

⁸This process quickly focuses the coder on a smaller number of relevant options while also allowing them to apply multiple tags if the sentence explicitly includes more than one or there is insufficient evidence to choose only one tag. The guided coding process also allows for the possibility that earlier coarse decisions have less error than later fine-grained decisions.

compounding, the ontology can capture what players were said to have known, learned, or said about other specific fully described actions.

[1] 37 17

Table 1: Ontological coverage of ICBe versus existing State of the Art

		Concept	Events Datasets						Episodes Datasets		
			MIDs	UCDP-GED	MIDs	ICFWS	ICB	COW	MIDs	ICB	Datasets
Domain	Players	Start (1–4)	1918	1945	1977	1995	1993	1989	1918	1816	1816
		End (5, 6)	2017	2019	2018	2020	2010	2015	2017	2014	2007
Pieces	Think	N	32k	8.5M	28.4M	17.5M	9.6K	128k	1K	5.9K	1K
		Coders	Hand	Automated	(CAMEO)		Hand	Hand	Hand	Hand	Hand
Say	Unarmed	Corpus	ICB	News		Mix	News	Mix	Mix	Mix	
		Date	Event	Article		Event	Article	Event	Event	Event	Event
Do	Armed	Location	Event	Event		Actor	Event	Actor	Event	Actor	Actor
		States (7–10)	✓	✓	✓	✓	✓	✓	✓	✓	✓
Say	Armed	Subnational Actors (11–14)	✓	✓	✓	✓	✓	✓	✓	✓	✓
		IGO/NGO (15–18)	✓	✓	✓	✓	✓				✓
Do	Armed	Civilians (19, 20)	✓	✓	✓	✓	✓	✓			
		Fatalities (21, 22)	✓				✓	✓	✓	✓	✓
Do	Armed	Force Size (23–25)	✓								
		Force Domain (26–29)	✓	✓	✓	✓					
Do	Armed	Geography (location, territorial change) (30)	✓								
		Alert (Start/End Crisis) (31)	✓								✓
Do	Armed	Wishes (Desire/Fear) (32, 33)	✓								✓
		Evaluation (Victory/Defeat) (34)	✓								✓
Do	Armed	Aims (Territory, Policy, Regime, Preemption) (35)									
		Awareness (Discover, Become Convinced) (36–38)	✓								
Do	Armed	React to past event (Praise, Disapprove, Accept, Reject, Accuse) (39–41)	✓	✓	✓	✓	✓	✓			
		Request future event (Appeal, Demand) (42)	✓	✓	✓	✓	✓	✓			
Do	Armed	Predict future event (Promise, Threaten, Express Intent, Offer Without Condition) (43, 44)	✓	✓	✓	✓	✓	✓			✓
		Predict with condition (Offer, Ultimatum) (45)	✓								
Do	Armed	Government (Leadership/Institution Change, Coup, Assassination) (46–50)	✓	✓	✓	✓	✓	✓			
		By Civilians (Protest/Riot/Strike) (51)	✓	✓	✓	✓	✓	✓			
Do	Armed	Against Civilians (Terrorism, Domestic Rights, Mass Killing, Evacuate) (52, 53)	✓	✓	✓	✓	✓	✓			
		Diplomacy (Discussion, Meeting, Mediation, Break off negotiations, Withdraw/Expel Diplomats, Propoganda) (54)	✓	✓	✓	✓	✓	✓			
Do	Armed	Legal Agreements (Sign Agreement, Settle Dispute, Join War on Behalf of, Ally, Mutual Defense Pact, Open Border, Cede Territory, Allow Inspections, Political Succession, Leave Alliance, Terminate Treaty) (55–57)	✓	✓	✓	✓	✓	✓			
		Violate Agreement (Violate Terms of Agreement) (58)	✓								
Do	Armed	Mutual Cooperation or Directed Aid (Economic cooperation or Aid, Military Cooperation, Intelligence Cooperation, Unspecified) (59)	✓	✓	✓	✓	✓	✓			
		Directed Aid (General Political Support, Economic Aid, Humanitarian Aid, Military Aid, Intelligence Aid, Unspecified Aid) (60, 61)	✓	✓	✓	✓	✓	✓			
Do	Armed	Preparation (Alert, Mobilization, Fortify, Exercise, Weapons Test) (62)	✓	✓	✓	✓	✓	✓			
		Maneuver (Deployment, Show of Force, Blockade, No Fly Zone, Border Violation) (63)	✓	✓	✓	✓	✓	✓			
Do	Armed	Combat (Battle/Clash, Attack, Invasion/Occupation, Bombard, Cease Fire, Retreat) (64, 65)	✓	✓	✓	✓	✓	✓			
		Strategic (Declare War, Join War, Continue Fighting, Surrender, End War, Withdraw from War, Switch Sides) (66, 67)	✓	✓	✓	✓	✓	✓			
Do	Armed	Autonomy (Assert Political Control Over, Assert Autonomy Against, Annex, Reduce Control Over, Decolonize) (68–70)	✓	✓	✓	✓	✓	✓			

Each crisis was typically assigned to 2 expert coders and 2 novice coders with an additional tie-breaking expert coder assigned to sentences with high disagreement.⁹ For the purposes of measuring intercoder agreement and consensus, we temporarily disaggregate the unit of analysis to the Coder-Crisis-Sentence-Tag ($n=993,740$), where a tag is any unique piece of information a coder can associate with a sentence such as an actor, date, behavior, etc. We then aggregate those tags into final events ($n=18,783$), using a consensus procedure (SI Appendix, Algorithm B2) that requires a tag to have been chosen by at least one expert coder and either a majority of expert or novice coders. This screens noisy tags that no expert considered possible but leverages novice knowledge to tie-break between equally plausible tags chosen by experts.

Internal Consistency

We evaluate the internal validity of the coding process in several ways. For every tag applied we calculate the observed intercoder agreement as the percent of other coders who also applied that same tag (SI Appendix, Fig. B3). Across all concepts, the Top 1 Tag Agreement was low among novices (31%), moderate for experts (65%), and high (73%) following the consensus screening procedure.

We attribute the remaining disagreement primarily to three sources. First, we required coders to rate their confidence which was observed to be low for 20% of sentences- half due to a mismatch between the ontology and the text (“survey doesn’t fit event”-45%) and half due to a lack of information or confused writing in the source text (“more knowledge needed”-40%, “confusing sentence”-6%). Observed disagreement varied predictably with self reported confidence (SI Appendix, Fig. B4). Second, as intended agreement is higher (75-80%) for questions with fewer options near the root of the ontology compared to agreement for questions near the leafs of the ontology (50%-60%). Third, individual coders exhibiting nontrivial coding styles, e.g. some more expressive applying many tags per concept while others focused on only the single best match. We further observed unintended synonymy, e.g. the same information can be framed as either a threat to do something or a promise not to do something.

Case Study Selection

The remaining two qualities we seek to measure are recall and precision of ICBe events in absolute terms and relative to other existing systems. We provide full ICB narratives, ICBe coding in an easy to read

⁹Expert coders were graduate students or postgraduates who collaboratively developed the ontology and documentation for the codebook. Undergraduate coders were students who engaged in classroom workshops.

iconographic form, and a wide range of visualizations for every case on the companion website. In this paper, we focus on two deep case studies. The first is the Cuban Missile Crisis (Figure 1) which took place primarily in the second half of 1962, involved the United States, the Soviet Union, and Cuba, and is widely known for bringing the world to the brink of nuclear war (hereafter Cuban Missiles). The second is the Crimea-Donbas Crisis (SI Appendix Figure D1) which took place primarily in 2014, involved Russia, Ukraine, and NATO, and within a decade spiraled into a full scale invasion (hereafter Crimea-Donbas). Both cases involve a superpower in crisis with a neighbor, initiated by a change from a friendly to hostile regime, with implications for economic and military security for the superpower, risked full scale invasion, and eventually invited intervention by opposing superpowers. We choose these cases because they are substantively significant to 20th and 21st century international relations, widely known across scientific disciplines and popular culture, and are sufficiently brief to evaluate in depth.

Recall

Recall measures the share of desired information recovered by a sequence of coded events, $Pr(E|H)$, and is poorly defined for historical episodes. First, there is no genuine ground truth about what occurred, only surviving texts about it. Second, there is no *a priori* guide to what information is necessary detail and what is ignorable trivia. History suffers from what is known as the Coastline Paradox (60) — it has a fractal dimension greater than one such that the more you zoom in the more detail you will find about individual events and in between every two discrete events. The ICBe ontology is a proposal about what information is important, but we need an independent benchmark to evaluate whether that proposal is a good one and that allows for comparing proposals from event projects that had different goals. We need a yardstick for history.

Our strategy for dealing with both problems is a plausibly objective yardstick called a synthetic historical narrative. For both case studies, we collect a large diverse corpus of narratives spanning timelines, encyclopedia entries, journal articles, news reports, websites, and government documents. Using natural language processing (fully described in SI Appendix, Algorithm C1), we identify details that appear across multiple accounts. The more accounts that mention a detail, the more central it is to understanding the true historical episode. The theoretical motivation is that authors face word limits which force them to pick and choose which details to include, and they choose details which serve the specific context of the document they are producing. With a sufficiently large and diverse corpus of documents, we can vary the context while holding the overall episode constant

and see which details tend to be invariant to context. Intuitively, a high quality event dataset should have high recall for context invariant details both because of their broader relevance and also because they are easier to find in source material.

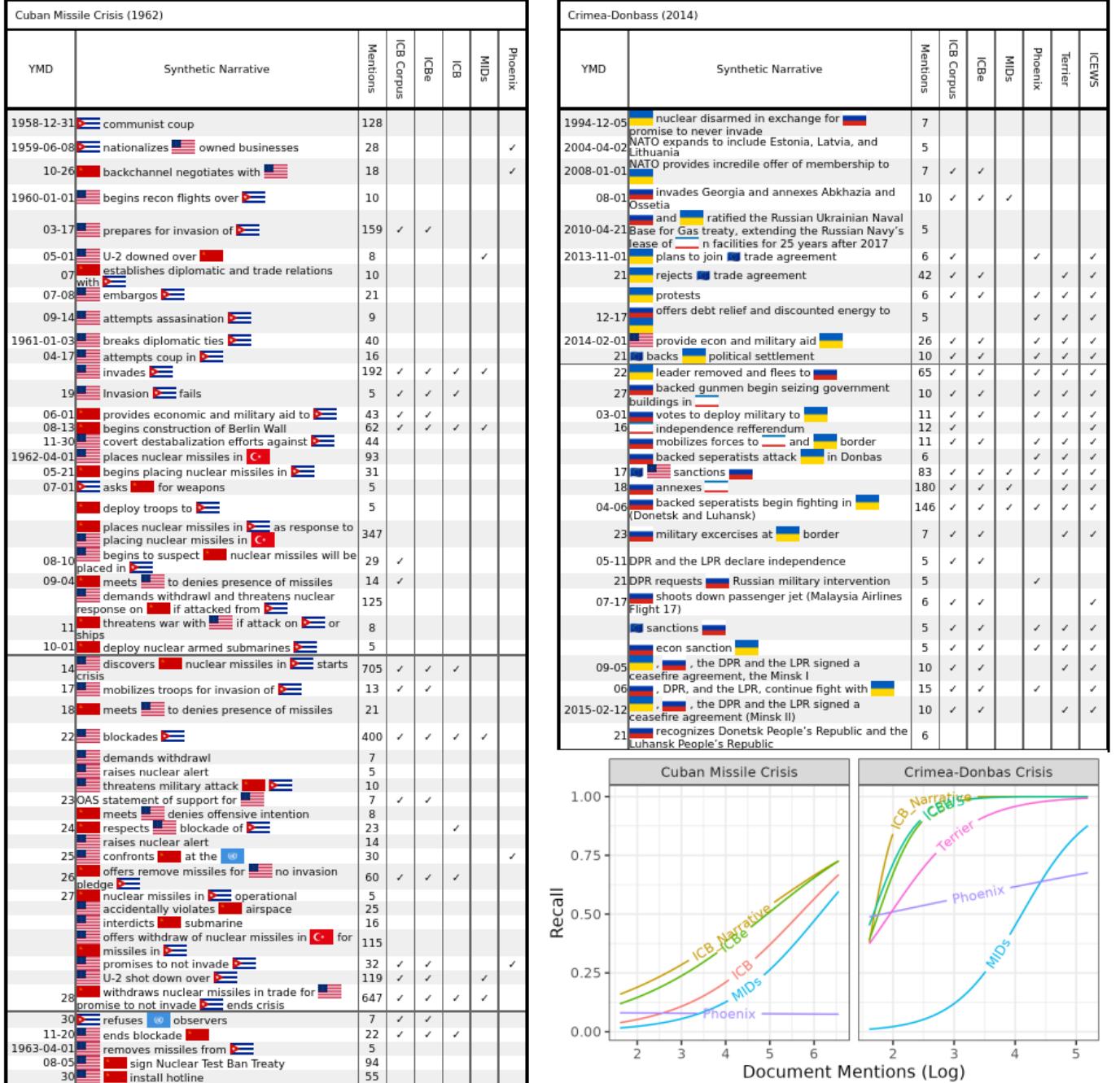
Synthetic historical narratives for Cuban Missiles (51 events drawn from 2020 documents) and Crimea-Donbas (30 events drawn from 971 documents) appear in Figure 2. Each row represents a detail which appeared in at least five documents along with an approximate start date, a hand written summary, the number of documents it was mentioned in, and whether it could be identified in the text of our ICB corpus, in our ICBe events, or any of the competing systems.

From them, we draw several stylized facts. First, there is substantial variation in which details any one document will choose to include. Our ground truth ICB narratives included 17/51 and 23/30 of the events from the synthetic narrative, while including other details that are not in the synthetic narrative. Second, mentions of a detail across accounts is exponentially distributed with context invariant details appearing dozens to hundreds of times more than context dependent details. Third, crisis start and stop dates are arbitrary and the historical record points to many precursor events as necessary detail for understanding later events, e.g. the U.S. was in a *de facto* grey scale war with Cuba before it invited Soviet military protection (61) and Ukraine provided several security guarantees to Russia that were potentially undone, e.g. a long term lease on naval facilities in Crimea. Fourth, we find variation between the two cases. Cuban Missiles has a cleaner canonical end with the Soviets agreeing to withdraw missiles while Crimea-Donbas meekly ends with a second cease fire agreement (Minsk II) but continued fighting. The canonical narrative of Cuban Missile also includes high level previously classified details, while the more recent Crimea-Donbas case reflects primarily public reporting.

We find substantive variation in recall across systems. Recall for each increases in the number of document mentions which is an important sign of validity for both them and our benchmark. The one outlier is Phoenix which is so noisy that it's flat to decreasing in mentions. The two episode level datasets have very low coverage of contextual details. The two other dictionary systems ICEWs and Terrier have high coverage, with ICEWs outperforming Terrier. ICBe strictly dominates all of the systems but ICEWs in recall though we note that the small sample sizes mean these systems should be considered statistically indistinguishable. Importantly our corpus of ICB narratives has very high recall of frequently mentioned details giving us confidence in how those summaries were constructed, and ICBe lags only slightly behind

showing that it left very little additional information on the table.

Figure 2: Measuring Recall with Synthetic Historical Narratives

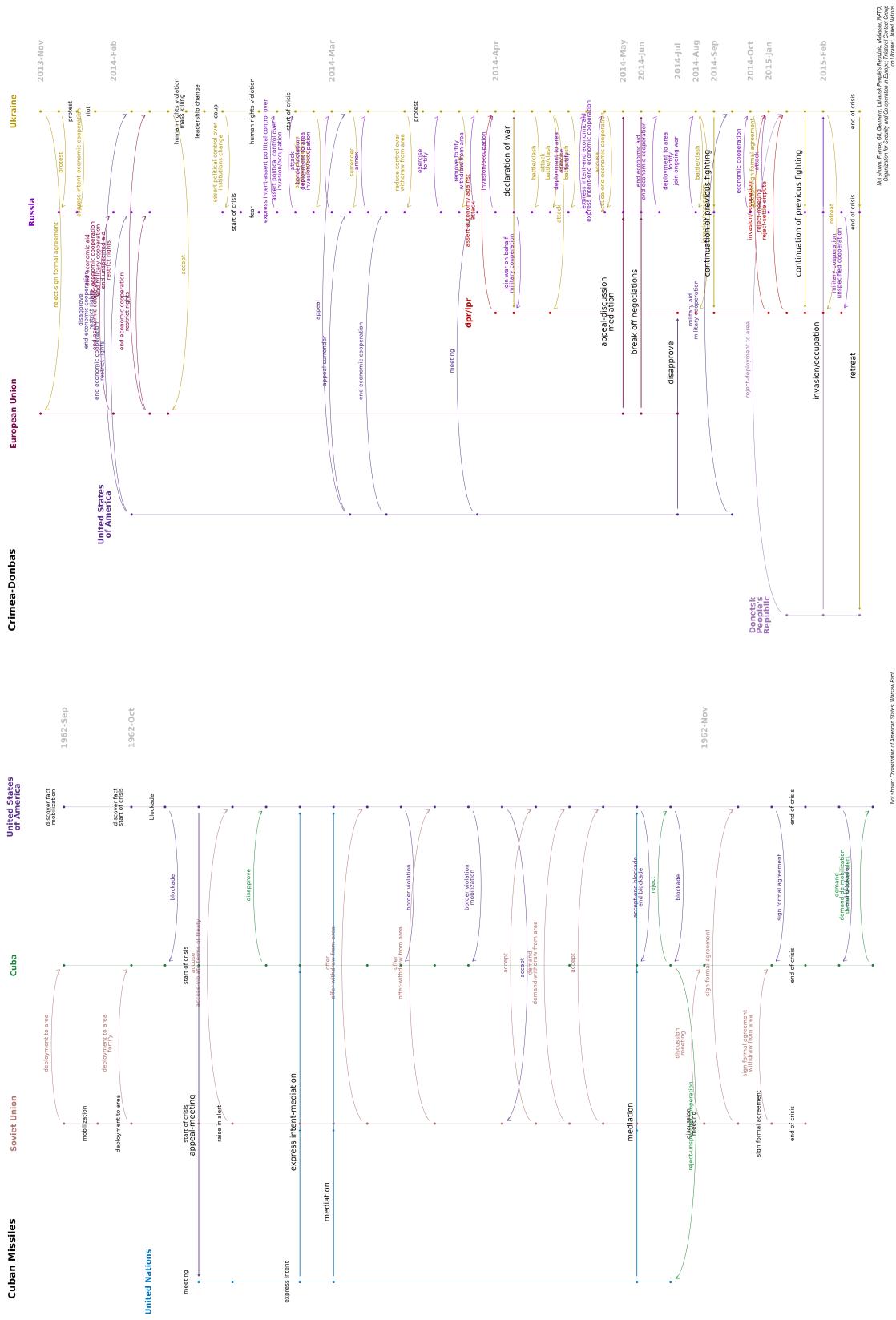


Notes: Synthetic narratives combine several thousand accounts of each crisis into a single timeline of events, taking only those mentioned in at least 5 or more documents. Checkmarks represent whether that event could be hand matched to any detail in the ICB corpus, ICBe dataset, or any of the other event datasets.

Precision

The other side of event measurement is precision, the degree to which a sequence of events correctly and usefully describes the information in history, $Pr(H|E)$. It does little good to recall a historical event but too vaguely (e.g. MIDs describes the Cuban Missile crisis as a blockade, a show of force, and a stalemate) or with too much error (e.g. ICEWS records 263 “Detonate Nuclear Weapons” events between 1995-2019) to be useful for downstream applications. ICBe’s ontology and coding system is designed to strike a balance so that the most important information is recovered accurately but also abstracted to a level that is still useful and interpretable. You should be able to lay out events of a crisis on a timeline, as in Figure 3, and read off the macro structure of an episode from each individual move. We call this visualization a crisis map, a directed graph intersected with a timeline, and provide crisis maps for every event dataset for each case study (SI Appendix, Fig. D3 and D4) and all crises on the companion website.

Figure 3: Crisis Maps



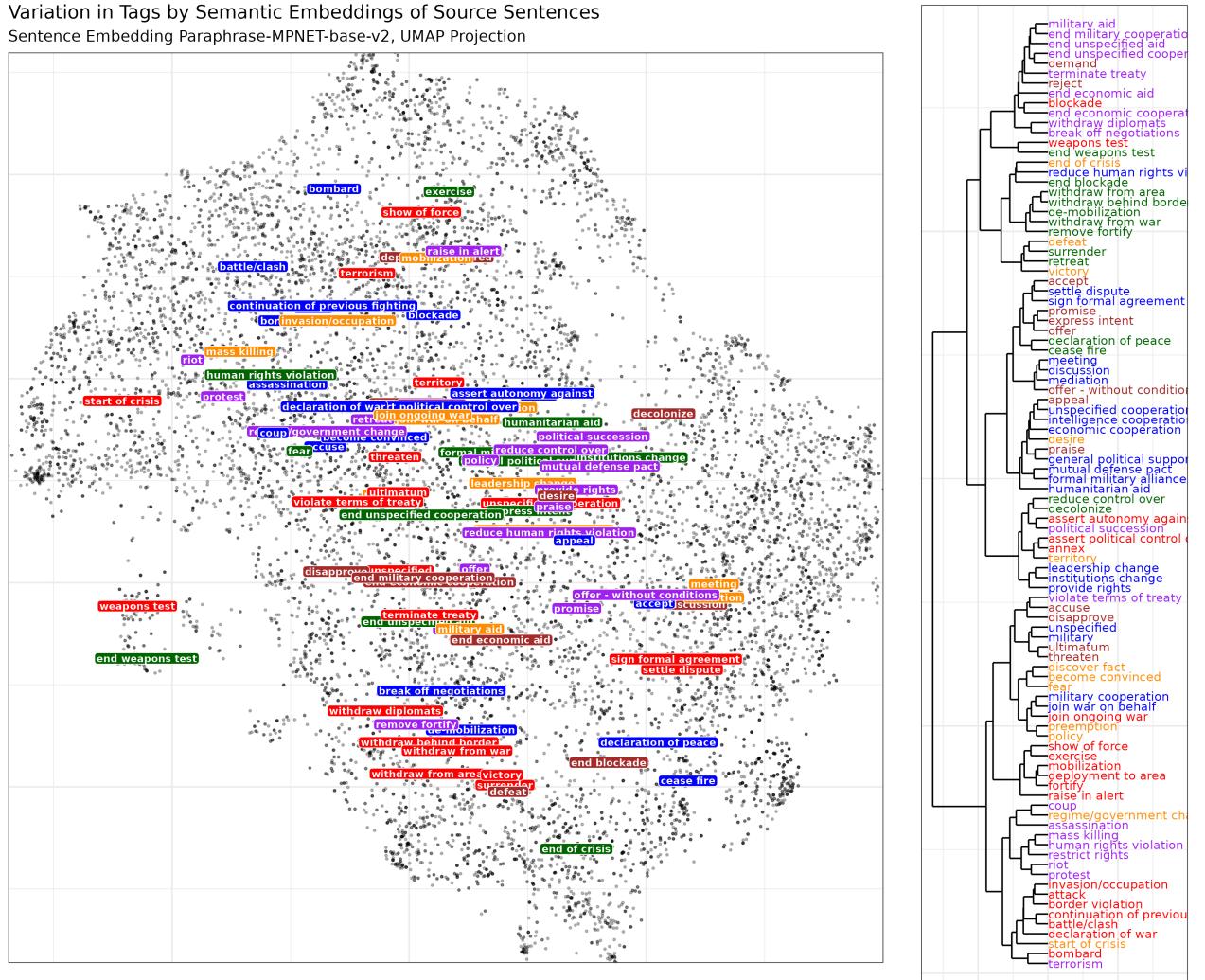
We further want to verify individual event codings, which we can do in the case of ICBe because each event is mapped to a specific span of text. We develop the iconography system for presenting event codings as coherent statements that can be compared side by side to the original source narrative as for Cuban Missiles (Figure 1), Crimea-Donbas (SI Appendix Table D1), and for every case on the companion website. We further provide a stratified sample of event codings alongside their source text (SI Appendix Table D2).

We find both the visualizations of macro structure and head-to-head comparisons of ICBe codings to the raw text to strongly support the quality of ICBe, but as with recall we seek a more objective detached universal benchmark. Our proposed measure is a reconstruction task to see whether our intended ontology can be recovered through only unsupervised clustering of sentences they were applied to. Figure 4 shows the location of every sentence from the ICBe corpus in semantic space as embedded using the same large language model as before, and the median location of each ICBe event tag applied to those sentences.¹⁰ Labels reflect the individual leaves of the ontology and colors reflect the higher level coerce branch nodes of the ontology. If ICBe has high precision, substantively similar tags ought to have been applied to substantively similar source text, which is what we see both in two dimensions in the main plot and via hierarchical clustering on all dimensions in the dendrogram along the righthand side.¹¹

¹⁰We preprocess sentences to replace named entities with a generic Entity token.

¹¹Hierchcial clustering on cosine similarity and with Ward's method.

Figure 4: ICBe event codings in comparison to Semantic Embeddings from source sentences



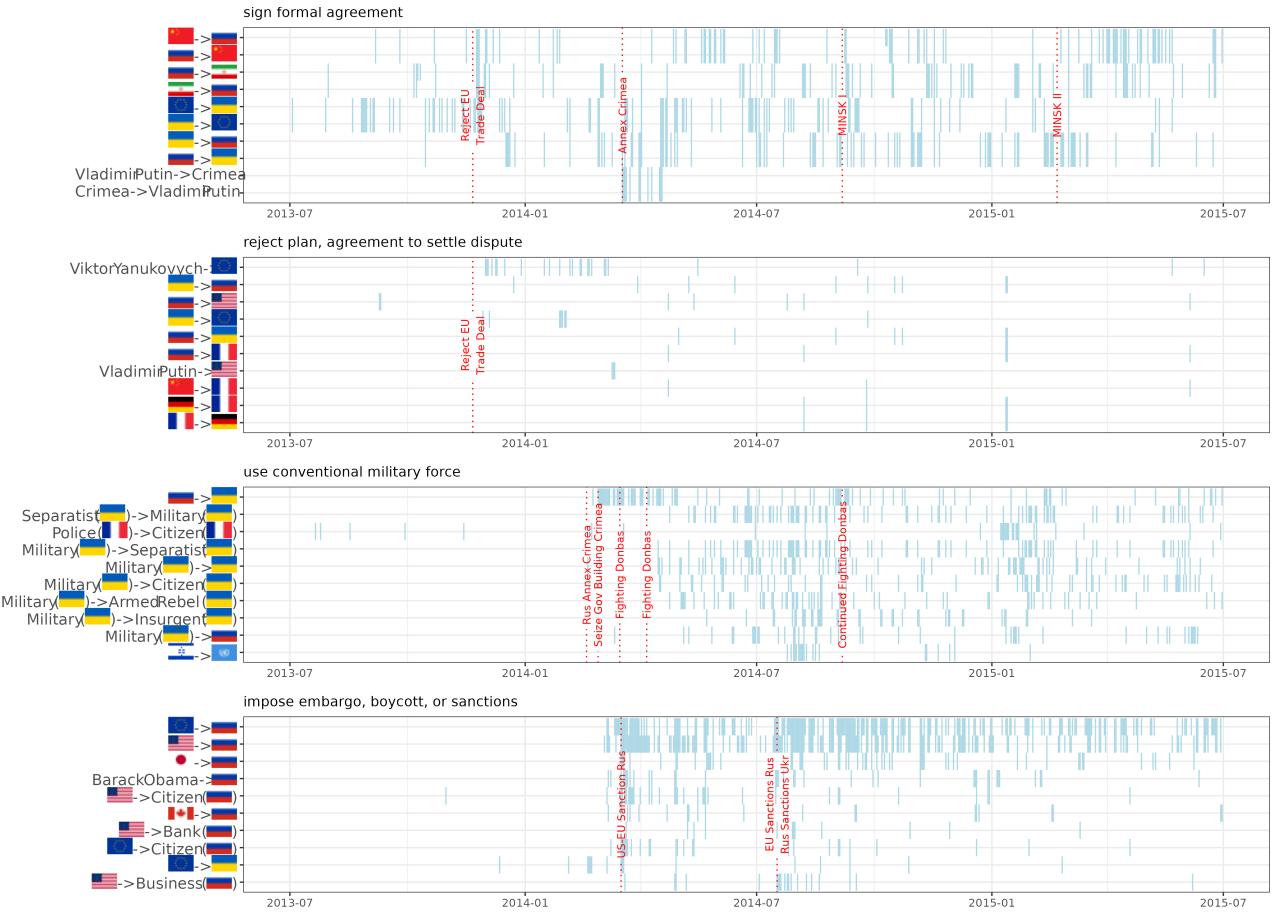
Notes: Dots represent individual ICB narrative sentences, as embeded by the Paraphrase-MPNET-base-v2 large language model and flattened into two dimensions with UMAP. Text labels reflect individual leaves of the ICBe ontology, and colors represent intermediate branches of the ontology. Label placement is the median of all of the sentences that tag was applied to by the coders. The dendrogram shows hierarchical clustering of the tags. If ICBe precision is high, the sentences tags were applied to ought to say similar things, and the intended shape of the ontology ought to be visually recognizable.

Finally, how does ICBe’s precision compare to the existing state of the art? The crisis-maps reveal the episode level datasets like MIDs or the original ICB are too sparse and vague to reconstruct the structure of the crisis (SI Appendix Figure D3 and D4). On the other end of the spectrum, the high recall dictionary based event datasets like Terrier and ICEWs produce so many noisy events (several hundreds thousands) that even with heavy filtering their crisis maps are completely unintelligible. Further, because of copyright issues, none of these datasets directly provide the original text spans making event level precision difficult to verify.

However, given their high recall on our task and the global and real-time coverage of dictionary based event systems, we want to take seriously the possibility that some functional transformation could recover the precision of ICBe. For example, (62) attempts to correct for the mechanically increasing amount of news coverage each year by detrending violent event counts from Phoenix using a human coded baseline. Others have focused on verifying precision for ICEWs on specific subsets of details against known ground truths, e.g. geolocation (63), protest events (80%) (64), anti-government protest networks (46.1%) (65).

We take the same approach here in Figure 5, selecting four specific CAMEO event codings and checking how often they reflect a true real world event. We choose four event types around key moments in the crisis. The start of the crisis revolves around Ukraine backing out of trade deal with the EU in favor of Russia, but “sign formal agreement” events act more like a topic detector with dozens of events generated by discussions of a possible agreement but not the actual agreement which never materialized. The switch is caught by the “reject plan, agreement to settle dispute”, but also continues for Victor Yanukovych for even after he was removed from power because of articles retroactively discussing the cause of his removal. Events for “use conventional military force” capture a threshold around the start of hostilities and who the participants were but not any particular battles or campaigns. Likewise, “impose embargo, boycott, or sanctions” captures the start of waves of sanctions and from who but are effectively constantly as the news coverage does not distinguish between subtle changes or additions. In sum, dictionary based methods on news corpora tend to have high recall because they parse everything in the news, but for the same reason their specificity for most event types is too low to back out individual chess like sequencing that ICBe aims to record.

Figure 5: ICEWs Events by Day by Type during the Crimea-Donbas Crisis



Notes: Unit of analysis is the Dyad-Day. Edges $<->$ indicates undirected dyad and $->$ indicates directed dyad. Top 10 most active dyads per category shown. Red text shows events from the synthetic narrative relative to that event category. Blue bars indicate an event recorded by ICEWs for that dyad on that day.

Conclusion

We investigated event abstraction from narratives describing key historical episodes in international relations. We synthesized a prior belief about the latent unobserved phenomena that drive these events in international relations and proposed a mapping to observable concepts that enter into the observed historical record. We designed an ontology with high coverage over those concepts and developed a training procedure and technical stack for human coding of historical texts. Multiple validity checks find the resulting codings have high internal validity (e.g. intercoder agreement) and external validity (i.e. matching source material in both micro-details at the sentence level and macro-details spanning full historical episodes). Further, these codings perform much better in terms of recall, precision, coverage, and overall coherence in capturing these historical episodes than existing event systems used in international relations.

We release several open-source products along with supporting code and documentation to further advance the study of IR, event extraction, and natural language processing. The first is the International Crisis Behavior Events (ICBe) dataset, an event-level aggregation of what took place during the crises identified by the ICB project. These data are appropriate for statistical analysis of hard questions about the sequencing of events (e.g. escalation and de-escalation of conflicts). Second, we provide a coder-level disaggregation with multiple codings of each sentence by experts and undergrads that allows for the introduction of uncertainty and human interpretation of events. Further, we release a direct mapping from the codings to the source text at the sentence level as a new resource for natural language processing. Finally, we provide a companion website that incorporates detailed visualizations of all of the data introduced here (www.crisisevents.org).

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