Dynamic Transactions Between News Frames and Sociopolitical Events: An Integrative, Hidden Markov Model Approach

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Abstract

A central goal of news research is to understand the interplay between news coverage and sociopolitical events. Although a great deal of work has elucidated how events drive news coverage, and how in turn news coverage influences societal outcomes, integrative systems-level models of the reciprocal interchanges between these two processes are sparse. Herein, we present a macro-scale investigation of the dynamic transactions between news frames and events using Hidden Markov Models (HMMs), focusing on morally charged news frames and sociopolitical events. Using 3,501,141 news records discussing 504,759 unique events, we demonstrate that sequences of frames and events can be characterized in terms of "hidden states" containing distinct moral frame and event relationships, and that these "hidden states" can forecast future news frames and events. This work serves to construct a path toward the integrated study of the news-event cycle across multiple research domain.

1. Introduction

A central goal of news research is to describe, explain, and predict the dynamic transactions between news and event occurrences (Chaffee & Berger, 1987; Thompson, 1995). Almost 100 years ago, Lippman (1922) began to call attention to how media messages shape the "pictures in our heads" of the outside world, setting the stage for a century of research investigating news media's role in shaping audiences' social and cognitive realities. Over the ensuing years, this research has proliferated into many subfields across psychology, journalism, communication, and other fields, producing clusters of research focused on news value theory (Galtung & Ruge, 1965), agenda setting theory (McCombs & Shaw, 1972), the spiral of silence (Noelle-Neumann, 1974), priming (Weaver, McCombs, & Spellman, 1975), and framing (Entman, 1993). This multiparadigmatic pluralism within news research has been demonstrated especially clearly within the domain of news framing. Research in this area integrates several subfields, including production, content, and effects of news (Entman, 1993; Matthes, 2009; Reese, 2007). In this sense, news framing provides a unique lens to examine how news shape and is shaped by societal events, and how news coverage influences, or even foments future events (D'Angelo, 2002; Gamson & Modigliani, 1989; Thompson, 1995).

While a number of studies show how reciprocal effects in news and framing research influence the social worlds of individual citizens (e.g., Schmuck et al., 2017), there are as yet few macro-level empirical assessments of the relationships between news framing and sociopolitical events (cf. D'Angelo, 2002; Gamson & Modigliani, 1989). This is in part due to the fact that large-scale datasets facilitating this sort of cross-disciplinary work have not previously been available. Further complicating this integrative endeavor, dynamic transactional processes are often non-linear, complex, and multidimensional (Priestley, 1988). Accordingly, assumptions of constant variance, homogeneity, or normality are often

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violated in the underlying data generating process. These factors have precluded the investigation of dynamic news-event transactions within a "monoculture of linear models" (Schrodt, 2014), exacerbating communication scholars' efforts to test integrative framing theories that postulate non-linear, reciprocal effects between news frames and event occurrences.

This study takes a step towards tackling these interlocking challenges. We obtain machine-coded news frames for 3,501,141 news records discussing a total of 504,759 sociopolitical events in the United States using the GDELT Interface for Communication Research (iCoRe; Hopp, Schaffer, Fisher, & Weber, 2019). Drawing on the Model of Intuitive Morality and Exemplars (MIME; Tamborini, 2012), we show that moral intuitions influence both frame-building and frame-setting processes, thus offering a bridge to examine news frames as antecedent and consequence of events. To assess the non-linear, complex, and high-dimensional dependencies across moral news frames and event occurrences, we leverage a sequence analysis method known as Hidden Markov Models (HMMs; Rabiner, 1989). Our results demonstrate that sequences of moral news frames and events can be described in terms of a relatively small number of "hidden states" characterized by distinct moral frame and event sequences. We show that these "hidden states" forecast future moral frames and events based on preceding moral frames and event sequences. Taken together, this work serves to highlight the combined, integrative utility of news framing and HMMs for analyzing recurrent patterns in large-scale news data, and to construct additional theoretical bridges between independently productive subfields of news research.

2. The Framing-Event Feedback System

2.1. How Events Drive Frames in the News

A substantial body of news research has examined how news coverage is shaped by unfolding sequences of sociopolitical events. Due in part to the myriad ways in which event occurrences shape journalistic *frame-building* processes (Cacciatore, Scheufele, & Iyengar, 2016; D'Angelo, 2002), there now exists an "impressive" (Kinder, 2007) number of definitions of what constitutes a *frame*. By abstracting and providing meaning to complex events, news frames have been conceptualized as "principles of organization" (Goffman, 1974, p. 10) or as a "central organizing idea or story line" (Gamson & Modigliani 1987, p. 143; 1989). Similarly, Entman's (1993) seminal definition entails that framing is to "select some aspects of a perceived reality and make them more salient" (p. 52).

Guided by this conceptual pluralism, the bulk of frame-building research highlights how particular types of sociopolitical events, including elections (Shah, Watts, Domke, & Fan, 2002), protests (McLeod & Detenber, 1999), economic turning points (de Vreese, Peter, & Semetko, 2001), and military conflicts (Reese & Buckalew, 1995) are portrayed by media outlets. News frames that discuss specific events and integrate them into the larger societal context have been referred to as *issue-specific* frames and are typically contrasted with *generic-news* frames that transcend topics and cultural contexts (de Vreese, 2012). Moreover, research has examined the ways in which controversial events lead to contesting journalistic news frames concerned with gaining an event's prerogative of interpretation (Chong & Druckman, 2007; Entman, 1991, 2003). News framing research has produced a broad body of knowledge elucidating how particular event types a) shape the ways in which media outlets abstract and simplify these events via issue-specific frames, b) elicit dissociable framing patterns across distinct types of news (e.g., Semetko & Valkenburg, 2000), and c) influence the course of congruent versus competing news frames. Notably, of particular importance to this special issue is ongoing research seeking to speak across both "event-driven frame-building" and "frame-driven event-building".

2.2. How News Frames Drive Real-World Events

In the previous section, we highlighted the role of news frames as dependent variables, i.e., as the outcome of media responses to independent event occurrences. Yet, media frames are also studied as independent variables, affecting audiences and shaping the course of future events (Cacciatore, Scheufele, & Iyengar, 2016). According to the integrated process model of framing (de Vreese, 2005), news frames bridge production of content (frame-building) with societal outcomes of content (frame-setting). Relatedly, the dynamic-transactional model (DTM; Früh & Schönbach, 1982) suggests that news outlets tend to follow "news-event careers"—states characterized by the usage of repetitive news frames to cover a given event or topic—until audiences either lose interest in the event or an external event occurs that changes the event-framing state of the initial event. Weber (1993) showed that these news-event careers are dominant in German prime time television news, highlighting that news outlets monitor television audience ratings and maintain or adjust event coverage accordingly. Other approaches such as McCombs and Shaw's (1972) agenda setting, Chong and Druckman's (2010) model on dynamic public opinion effects, Entman's (2003) cascading activation, and Slater's (2007) reinforcing spirals postulate similar transactional mechanisms. Analogously, research on media hype and news waves demonstrates that at times, the way that news media frame certain events can influence the nature of ensuing events (Thompson, 1995; Vasterman, 2005).

In each of these frameworks, it is recognized that a frame's transactional effect is contingent upon its motivational relevance for both production and consumption of news (de Vreese, 2005, 2012). Chong and Druckman (2007), for instance, note that such framing effects depend on a variety of factors, including, but not limited to the strength or repetition of the frame, the framing environment, and individual motivations. Moreover, a growing body of literature discusses what sort of frames affect individual cognitions and behavior (e.g., Gross, 2008; Iyengar & Simon, 1993) and how long these effects last (Baden, & Lecheler, 2012).

3. Moral Intuitions Permeate Frame-Building and Frame-Setting

Although the previously discussed literature demonstrates brisk progress toward understanding how events influence frame-building, and how frame-setting influences events, integrated assessments between specific types of news frames and sociopolitical events remain sparse (cf. D'Angelo, 2002; Gamson & Modigliani, 1989). We contend that moral intuitions serve as promising test bed for developing a holistic perspective on news frames as both antecedent and consequence of events. Moral intuitions permeate the news cycle (Altheide, 1997) and robustly influence both frame construction and framing effects (Bowman, Lewis, & Tamborini, 2014; Lewis, Grizzard, Bowman, Eden, & Tamborini, 2011; Tamborini & Weber, in press). Moreover, audiences obtain a majority of information about their worlds via news media (Gerbner & Marvanyi, 1977) and frequently focus on the moral intentions behind policies (Morgan et al., 2010). Because of this, it is likely that moral intuitions offer a path for understanding how "the media shape and influence the course of events, and indeed, create events that would not have existed in their absence" (Thompson, 1995, p.117).

The Model of Intuitive Morality and Exemplars (MIME; Tamborini, 2012) provides a theoretical framework to examine the reciprocal relationship between moral news frames and audience responses. The MIME postulates that audiences evaluate news based on moral frames and in turn journalists tailor messages to be congruent with audiences' moral sensibilities (Bowman, et al., 2014). Mounting evidence suggests that moral intuitions are salient across media content, including news (Weber et al., 2018). Likewise, moral intuitions serve as a monitoring system to enforce behaviors that yield optimal outcomes for society as a whole (Buckholtz & Marois, 2012). Hence, during news exposure, moral intuitions have been shown to yield an intuitive pleasure response when a behavior is observed that upholds moral norms, and a displeasure response when moral norms are violated (Lewis, et al., 2011). In addition to evaluative responses, growing evidence demonstrates the *behavioral* effects of exposure to moral frames. Messages that contain moral frames are shared more widely (Valenzuela et al., 2017) and are more likely to spur violence during protest movements (Mooijman, Hoover, Lin, Ji, & Dehghani, 2018).

4. Retrieving News Frames and Sociopolitical Events with iCoRe

The GDELT Interface for Communication Research (iCoRe; Hopp et al., 2019) facilitates the integrated study of moral news frames and events by providing simplified, fast access to the Global Database of Events, Language, and Tone (GDELT; Leetaru & Schrodt, 2013). Since its initial development in 2013, GDELT has monitored, stored, and computationally content-analyzed millions of online newspaper articles from sources around the world. Content-analytic measures of each article are obtained via a variety of dictionary-based methods (Grimmer & Stewart, 2013). This makes GDELT amenable to a substantial amount of computer-assisted framing research using similar dictionary-based approaches to operationalize news frames in terms of “the presence or absence of certain keywords" (Entman, 1993, p. 52). Beyond dictionary-based frame extraction, GDELT relies on the Conflict and Mediation Event Observation (CAMEO; Gerner, Schrodt, Yilmaz, & Abu-Jabr, 2002) codebook to extract mentions of various sociopolitical event types (e.g., protests, speeches, elections, etc.).

To date, GDELT’s content analytic measurements have proven helpful for examining inter-media agenda-setting effects (Guo & Vargo, 2017; Vargo & Guo, 2017) and fake news (Guo & Vargo, 2018; Vargo, Guo, & Amazeen, 2018). Likewise, GDELT’s automatically extracted events have been shown to be helpful in a variety of event forecasting models (e.g., Petroff, Bond, & Bond, 2013; Qiao et al., 2017). For the purposes of the current study, we seek to integrate both news frames and event occurrences to probe their dynamic transactions.

5. Examining Transactions Between News and Events Using Hidden Markov Models

Dynamic transactional processes, such as those that occur in the news-event cycle, are frequently non-linear, complex, and multidimensional (Priestley, 1988). These complexities, although long stymieing productive investigation in this domain, can be addressed using analytic tools designed to handle large, noisy sequences of data. Hidden Markov Models (HMMs; Rabiner, 1989) are a class of probabilistic sequence models designed for just this purpose. HMMs are used to classify sequences of observations into discrete categories referred to as *states.* Importantly, the states in a HMM are conceptualized as latent and hence not directly observable. Each state is comprised of a number of observable *symbols*, each of which has a certain *emission probability*, denoting the likelihood that a particular symbol will be observed in a particular state. Transitions from one state to any of the other possible states are predicted by a *transition probability.*

Given an input sequence of observations, an HMM computes a probability distribution over all possible sequences of states and chooses the label sequence that most accurately fits the observed data. To illustrate, one could use an HMM to classify an hourly log of temperature, humidity, and other climate data (symbols) over the course of a year into discrete seasons (states). In this example, a certain type of symbol (such as a temperature over 100°F) would be assigned a higher emission probability for a “summer” state than for a “winter” state, and as such an observed sequence of many 100°F days in a row would likely garner a "summer" classification. This "summer" state would have a higher probability to transition into a "fall" state (characterized by warm but falling temperatures) than into a "spring" state (characterized by cool but rising temperatures).

The utility of HMMs for integrating frame-building and frame-setting within framing research lies primarily in the fact that these models afford robust, data-driven modeling capabilities while also allowing researchers to manipulate parameters of interest in a theory-driven fashion. HMMs can be used to learn how different states are associated with different densities of news frames, as well as the distribution of event types that are associated with a given state. In this sense, it becomes possible to determine what sorts of news frames and event types are most likely to be perceived *together,* and how their co-occurrence patterns can give rise to particular latent states. Finally, by learning the transition probabilities between states, HMMs can *predict* the next state–and its associated moral frames and event types–that is most likely to follow from the state one is currently in. This news-event forecasting is accomplished via the generative capacity of HMMs, which allows to sample a sequence of most likely ensuing news frames and event types based on the model's present state.

6. Method

All data, code, and supplemental information (*SI*) have been made publicly available via the Open Science Framework and can be accessed at https://osf.io/ab2s3/.

6.1. GDELT Interface for Communication Research (iCoRe)

6.1.1. Data ingest and filtering

Data for this analysis was obtained using the GDELT Interface for Communication Research (iCoRe, Hopp et al., 2019, http://icore.medianeuroscience.org). We downloaded all GKG (GDELT Knowledge Graph) news records published by U.S. outlets from January 1st 2016 until September 30th 2018. iCoRe currently whitelists the top 34 U.S. news sources with the highest global online reach (see Table 2 in *SI* for an overview). In total, this query returned 3,501,141 GKG records. For each unique event present in the database, GDELT records the number of times this event has been reported across all monitored sources within the first 15 minutes of its occurrence, serving as a proximate measure of the event's importance. In an attempt to exclude insignificant events, we excluded events that were not mentioned in at least 10 articles (3rd quartile). As a final step, we filtered the GKG records to only include articles that mentioned these selected events. This was achieved by only including GKG records whose URL was associated with a recorded event that received significant coverage, indicated by the previously described mention filter.

6.2. Variables and Preprocessing

6.2.1. Moral news frames

In order to extract keywords pertaining to moral intuitions, we relied on GDELT's implementation of the Moral Foundations Dictionary (MFD; Graham et al., 2009). The MFD contains word lists pertaining to the five moral foundations as defined by Moral Foundations Theory (Graham et al., 2009): *Care, Fairness, Loyalty, Authority,* and *Purity*. The MFD further subdivides these foundations into *virtue* and *vice* word lists to reflect moral adherences versus moral violations. For example, the word *protect* indicates care-virtue whereas *hurt* indicates care-vice. This dictionary approach provides a count on how many words of a given news article fall into the virtue or vice category for each moral foundation. Furthermore, although not the primary focus of this paper, we complement these moral news frames with three emotional frame categories referencing *Anxiety, Anger,* and *Sadness* as indexed by GDELT's implementation of the Linguistic Inquiry and Word Count (LIWC; Pennebaker, Francis, & Booth, 2001).

6.2.2. Event types

We utilized GDELT's automatic event extraction facilitated via the CAMEO coding scheme (Gerner et al., 2002) to obtain daily counts of various event types happening within the United States. The CAMEO coding scheme allows for aggregating event types at various levels of specificity (e.g., event code 0811 reflects *ease restrictions on political freedoms*, which belongs to the event root category 08 pertaining to the event type *YIELD*), and we aggregated all event types according to their root codes, which leaves a total of 20 different event types. In total, 504,759 unique events were retrieved (see Table 3 in *SI* for frequencies and descriptions of each event type).

6.3. Sequence Analysis of Moral News Frames and Real-World Events

To analyze the dynamic transactions between moral news frames and real-world events, we rely on Hidden Markov Models (HMMs; Rabiner, 1989). We conceptualize societies as transitioning through hidden states (e.g., peaceful, conflictive, escalating, etc.) that are defined by distinct, observable distributions of moral news frames and event types. Hence, news frames and event types are modeled as a set of observable symbols with emission probabilities B. Initial state changes (i.e., before the HMM has been trained) occur with a preset matrix of transition probabilities π. After the HMM has been trained, these state changes are referred to as the transition probabilities A. Taken together, HMMs are commonly expressed using the shorthand notation $\lambda = (A, B, \pi)$.

6.4. Data Development

6.4.1. Symbol sets and sequence building

We trained two different HMMs. The first model (called L for large) consisted of a total of 33 symbols (20 event codes, 13 frame codes), whereas for the second HMM (called S for small), we relied on GDELT's event quad class variable and associated each of the 20 CAMEO event types with one of four symbols (*Material Conflict, Material Cooperation, Verbal Conflict,* and *Verbal Cooperation*), thus producing a total of 19 symbols (four event codes, 13 frame codes; see Table 4 in *SI* for event-symbol mappings). We primarily used model L to derive a more fine-grained assessment of the particular event types that co-occur with moral news frames. Model S was utilized for our news-event predictions. The smaller set of event-symbol mappings in model S served to increase the feasibility of our classifications (Petroff et. al, 2013), and to reduce the potentially detrimental influence of sporadic errors introduced by GDELT's automated codings (Wang, Kennedy, Lazer, & Ramakrishnan, 2016).

Next, we associated each category in the MFD with one moral frame symbol, creating a total of ten moral frame symbols. We mapped each of the three emotional news frames contained in LIWC to an emotional frame symbol. Next, we extracted one moral frame symbol per GKG record according to the frame category that received the highest word count. If an article contained no words pertaining to any of the news frame categories, a *Null Frame* symbol was implemented for that time stamp. By following this logic, we maintained a discrete HMM across news frames and event symbols, which allowed us to draw on discrete probability density functions to compute the emission probabilities for each state. In a final step, we placed event and frame symbols into a sequence in which events are observed every full hour and the news frame symbol discussing that event at half an hour intervals, thereby fulfilling the assumption of HMMs that its symbols are equally spaced in time (Rabiner, 1989). This sequential ordering is also logically valid as, *ceteris paribus*, events typically happen before a news article discusses them. Rather than training a HMM on one fully connected sequence, we experimented with different sequence lengths consisting of weekly and monthly chunks to increase the number of possible iterations in the training algorithm (see HMM training below) and to test the predictive accuracy of the model in news-event predictions. In a final step, we split the data input stream into a training set (January 1st 2016 to December 31st, 2017) and a test set (January 1st 2018 to September 30th, 2018).

6.4.2. States

The number of states in a HMM is a hyperparameter, similar to selecting the number of *k* clusters in a cluster analysis. Generally, the greater the number of selected states, the higher the predictive accuracy and the higher the risk of overfitting. Accordingly, we set out to choose a number of states that achieves satisfactory predictive accuracy on a hold-out set and maintains substantial interpretability of the model. Although the states in an HMM are hidden and thus cannot be directly observed, we conceived of these states as phases through which a society transitions. For example, when observing mounting social protests along with moral news frames highlighting the social injustice within a society, we may consider ourselves to be in a state of social unrest. Following previous approaches (e.g., Petroff et al., 2013; Qiao et al., 2017), we have settled on a four state, unsupervised model for model *L* and a five state, semi-supervised for model *S* (for rationale, see *SI*). In the unsupervised model, the algorithm computes all emission and transition probabilities directly from the data, whereas in the semi-supervised model, we set the emission probabilities manually (see HMM training below).

6.5. HMM Training (Baum-Welch Estimates)

Initiation, training, and evaluation of the HMM were conducted in Python using the *pomegranate* library (Schreiber, 2017). We briefly describe the algorithm for initiating each HMM (a more elaborate discussion is provided in the *SI*). The Baum-Welch training algorithm starts with a sequence of observations (nominal news frames and events represented as discrete symbols). From this input, the most likely set of state transition probabilities along with their likely symbol distributions and initial state transition probabilities is computed. The main difference between the unsupervised model *L* and semi-supervised model *S* is the following: For *L*, the model learns all parameters directly from the input sequence, whereas for *S*, we derive the initial state transition probabilities empirically by counting each of the possible symbol pairs in the input stream and dividing by the total. Furthermore, in *S*, we label the states as *conflictive*, *escalating*, *de-escalating*, *peaceful*, and *background*. Accordingly, we assume that certain symbols are more likely to be observed when being in particular states compared to others and hence adjust the emission probabilities accordingly (See Table 1). For example, when being in the de-escalating state, the probability to observe either Verbal Cooperation, Authority, or Loyalty symbols should be higher than observing any of the remaining 16 symbols.

State	Conflictive	Escalating	De-escalating	Peaceful	Background
Polarity	Very Negative	Negative	Positive	Very Positive	Neutral
Symbols	Material Conflict Harm Betrayal Degradation Anger	Verbal Conflict Subversion Cheating Anxiety Sad	Verbal Cooperation Authority Loyalty	Material Cooperation Care Fairness Sanctity	Null Event Null Frame

Table 1. Symbol Mappings for Deriving Initial Transition and Emission Probabilities. Symbols in each respective state have a higher emission probability than other symbols that are not in that state. The emission probability of foreign-state symbols decreases according to the distance of the state on the polarity continuum.

6.6. Forecasting

After training model *S*, we wrote a custom algorithm using the HMM to forecast news frame-event sequences (see *SI*). Thereby, in addition to predicting the correct *order* of symbols, we also examined how accurate our HMM can predict the *density* of events and news frames in the following week based on the density of the previously observed week. For this task, we recorded the total number of each symbol generated for the respective prediction period divided by the total number of generated symbols for this period to obtain a relative frequency of forecasted symbol types. We ascertained the performance by examining how accurately the forecast captured the overall density for event types and news frames and the direction of the trend (for a similar approach, see Petroff et al., 2013).

7. Results

7.1. Event Detection, Selection, and Moral Framing

Before evaluating the HMMs, we provide a short validation and visualization of GDELT's variables that are of interest to this study. First, spikes in GDELT's event data correspond to real-world events that were happening at that time point (Figure 1A). For example, spikes in articles discussing PROTEST events were highest for November 10th, 2016, the day after Donald Trump's presidential election (for validations of other events in GDELT, see Hopp et al., 2019; Qiao et al., 2017). Furthermore, Figure 1B illustrates that there are significant differences in the frequency of news sources that report on particular events, demonstrating the existence of news values during event selection. While public statements and events that involve fights or coercion are among the most frequently reported events, protest and events involving appeal and cooperation typically receive less coverage. In addition, we contrasted the moral framing of several event types (Figure 1C) and found that there are statistically significant, theoretically-congruent differences among the moral framing of events based on the MFD. FIGHT events are discussedwith higher mentions of *Harm*, whereas PROTEST events are mentioned more frequently with words that indicate *Subversion*, while APPEAL and PROVIDE AID events generally are discussed with agreater reliance on *Care* words, demonstrating the general construct validity of the MFD.

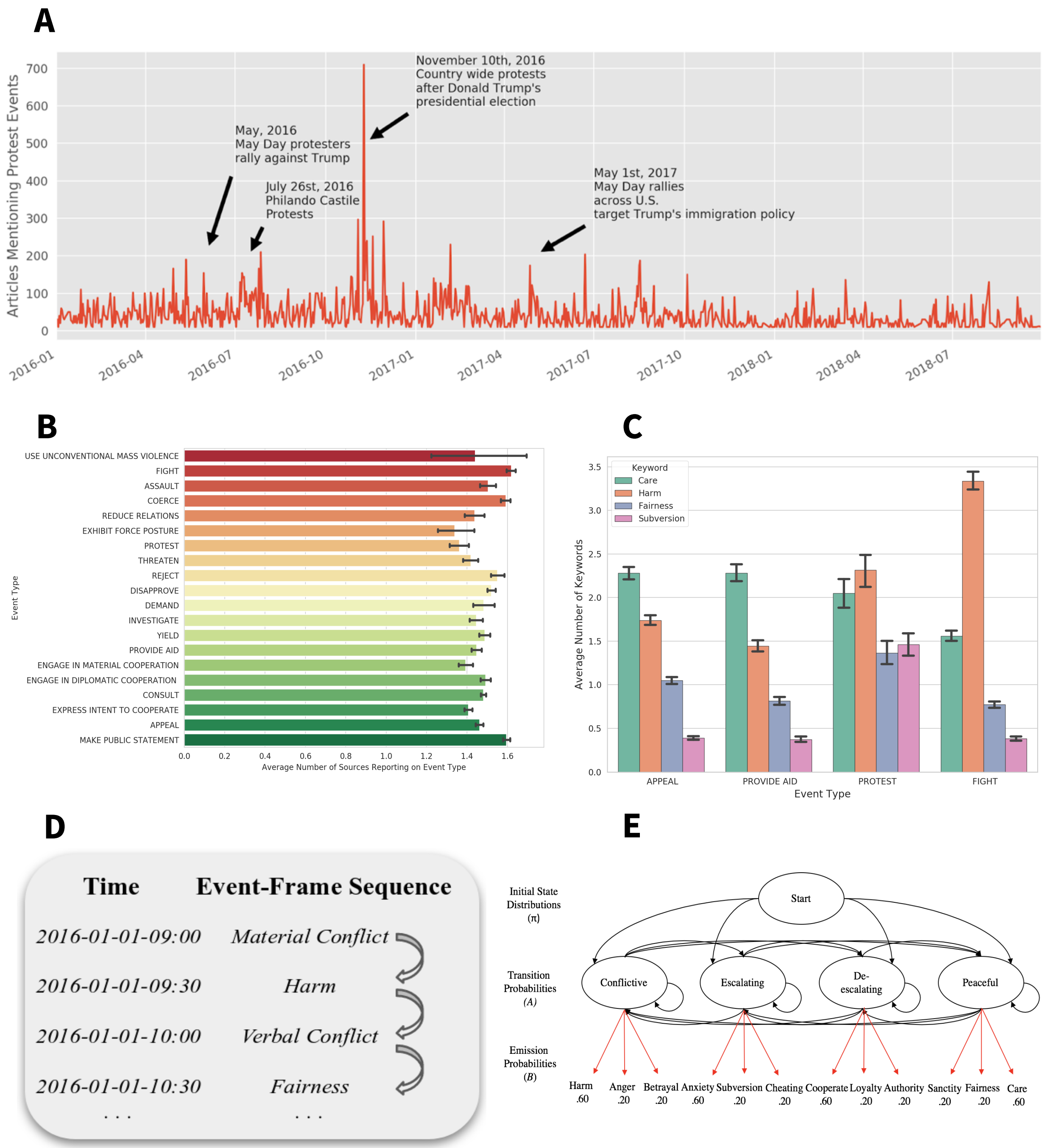

Figure 1. Event Detection, Event Selection, Moral Framing, and Event-Frame State Transitions **A**. Articles mentioning protest events in the United States from January 1st 2016 -- September 1st, 2018. **B**. Average number of news sources reporting on distinct event types. Event types are color coded according to their Goldstein index, with green colors reflecting a more positive score and red colors reflecting more negative scores. **C**. Differences in average keyword counts across selected moral keyword categories and event types. **D**. Event-frame sequence alignment. **E**. Frame-event states as HMM, with circles reflecting states. Error bars in **B** and **C** reflect 95% confidence intervals estimated with 1,000 bootstrap iterations.

7.2. Dynamic Transactions between Moral News Frames and Events

Next, we evaluate the learned transactions between moral news frames and event occurrences in the unsupervised HMM (model *L*). Figure 2A illustrates the learned news frame-event states, along with the emission probabilities for observing each symbol when being in that state. Evaluating these latent states, we first find that there exist diverse symbol distributions across states, providing compelling evidence that there are distinct patterns of dynamically occuring moral news frames and events. When evaluating these distributions closer, we can observe that in state s_0, there are transactions between FIGHT and APPEAL events together with news articles discussing *Harm* and *Subversion*, suggesting the heightened co-occurence of these symbols during particular sequences in the news-event cycle. Furthermore, states s_1 and s_3 are characterized by news-event cycles that contain higher frequencies of CONSULT and COOPERATION events, with a greater likelihood of observing moral news frames pertaining to *Loyalty,* indicating that news coverage during these media cycles influences and is shaped by a greater likelihood of events that aim at international cooperation.

In addition to learning the emission probabilities for each state, Figure 2B and 2C highlight the state transition probabilities. As a reminder, these indicate how likely the model is to transition into a particular news-event cycle given the current state that the model currently resides in. Because we have a fully-connected (i.e., ergodic) HMM, it is possible to transition from any state to any other state, including self-loops where the model remains in the same state. While the substantial interpretation of these transition probabilities is difficult due to our large symbol set, we do observe interesting dynamics, for example, between states s_0 and state s_3. Here, the model is more likely to transition from a more "conflictive" state (s_0) to a state that is characterized by a news-cycle with a greater density of news and events emphasizing cooperation and in-group alliance than the other way around. However, as we show in the next sections, these transition probabilities have greater informative value when one is trying to predict *subsequent* news frames and events based on the current news-cycle that the model resides in.

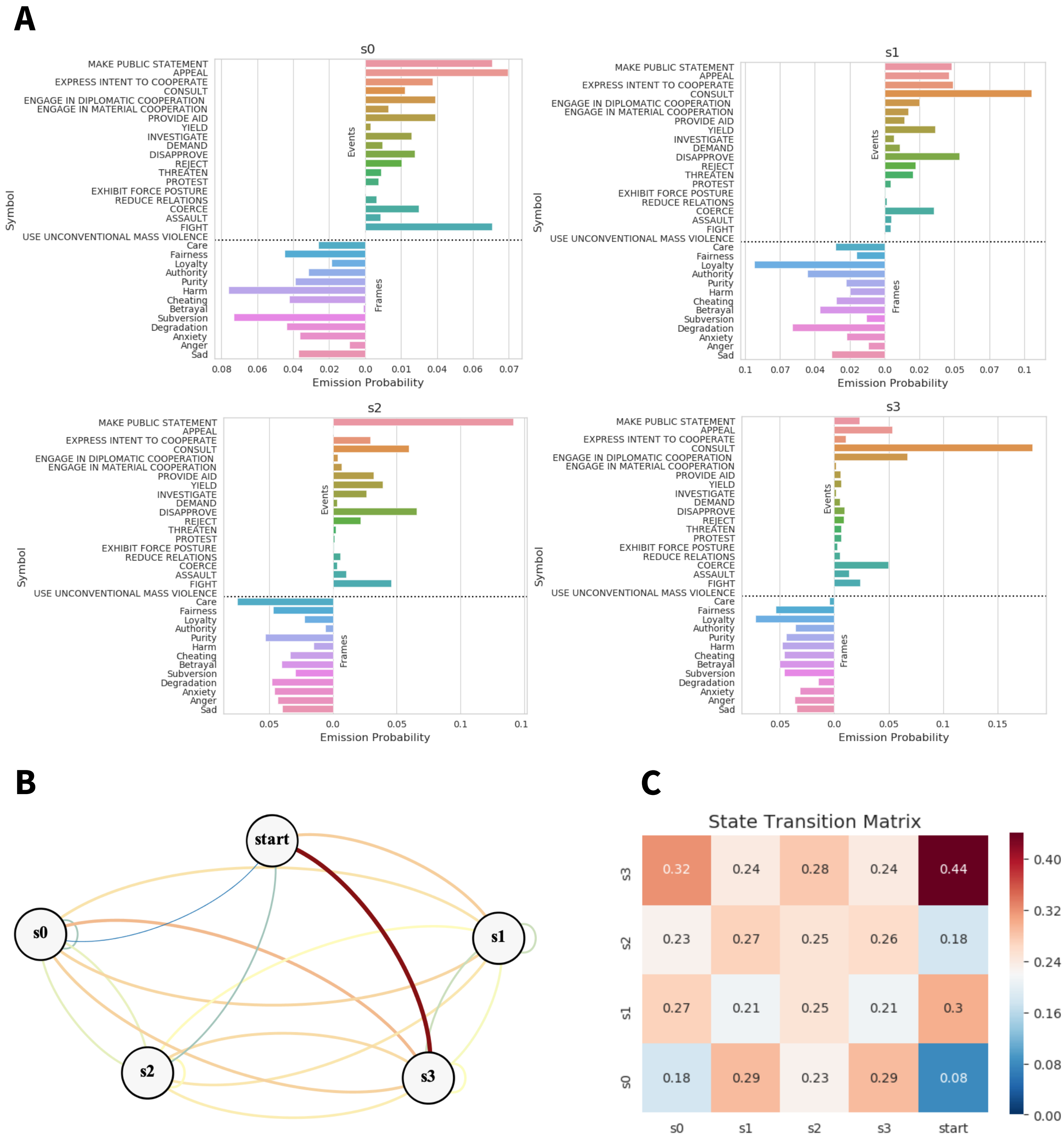

Figure 2. Learned Event-Frame States, Emission Probabilities, and State Transitions. A. Learned states of HMM with emission probabilities for each event and frame symbol B. Graph representation of HMM, edge weights reflect transition probabilities C. Transition matrix.

7.3. Sequence Prediction of Moral News Frames and Events

All of the following analyses are based on the semi-supervised HMM. To evaluate how well this model can predict subsequent news frame and events, we used confusion matrices that store the predicted symbol and compare it to the actual symbol in the test sequence. The following performance measures were used: specificity (true negative rate), precision (positive predictive value), and sensitivity (true positive rate). We found that a maximum number of three iterations in the Baum-Welch training algorithm produced highest event prediction scores (precision = 0.242, sensitivity = 0.241, specificity = 0.817), whereas a longer training of eight iterations was optimal for frame symbol prediction (precision = 0.089, sensitivity = 0.088, specificity = 0.933). For the interpretation of these scores, it is important to note that event and frame accuracies cannot be directly compared, since their respective confusion matrices consist of a different number of categories. Whereas the HMM has to correctly predict one out of five event symbols in the sequence P(chance agreement) = 0.2, the HMM has to correctly predict one out of 14 frame symbols P(chance agreement) = 0.05. Yet, given that both event and frame predictions result in precision accuracies that are above chance with respect to both event and news frame predictions, this finding provides evidence that future news frame and event occurrences can be predicted by learning the transactions among previously observed news frames and events.

Further, when examining the respective confusion matrices for events and frames, it becomes noticeable that the model most accurately predicts symbols that appear most frequently in the input stream (e.g., null observations, verbal cooperation events, and news frames surrounding the moral foundation of loyalty), but simultaneously confuses other, less frequently appearing symbols (e.g., material conflict events, news frames surrounding the moral foundation of purity) most often with more frequently appearing symbols.

7.4. Forecasts of Densities and Trends in Moral News Frames and Events

To evaluate how accurately HMMs can predict trends in the density of certain symbol types, we relied on the HMM optimized for event predictions (Table 6 in *SI* illustrates the evaluation of our event and frame trend predictions). We computed the root mean squared error (RMSE) between observed and predicted symbol densities as a direct measure of our model's predictive accuracy. Furthermore, we also computed the degree to which the model captures the correct trend in symbol densities for the following weekly time period. Overall, the results are promising: The HMM was able to predict the correct trend in symbol densities from seven out of our nineteen symbol types with above chance-accuracy (See Table 2). The model achieved highest accuracy for predicting the material conflict event type, with a correct direction of the density trend in 71.79% of cases. Figure 3 provides a visualization of the resulting time series for the observed versus predicted material conflict densities. As can be seen, the model performs particularly well from March to June 2018, months which witnessed a high frequency of political and civil conflicts surrounding gun violence (e.g., *March for Our Lives*, March 24th, 2018) and the Trump administration's "zero tolerance" policy (e.g., *Families Belong Together*, May -- June, 2018). Finally, we contrasted the trend prediction accuracy of our HMM across various alternative baseline models (consult *SI* for rationale and comprehensive evaluation of baseline models), demonstrating that our HMM outperforms null models in aggregate trend predictions by 11.28% and up to 15.38% for the most well predicted symbol type (material conflict events).

Symbol	RMSE	Correct Trend (%)
Material Conflict	0.007	71.79
Verbal Cooperation	0.02	66.67
NullFrame	0.038	58.97
NullEvent	0.02	56.41
Care	0.00	56.41
Anger	0.024	51.28
Loyalty	0.048	51.28

Table 2. *Trend Forecast Evaluation for January 1st 2018 to September 30th, 2018.* Only symbols with above chance trend classification are illustrated.

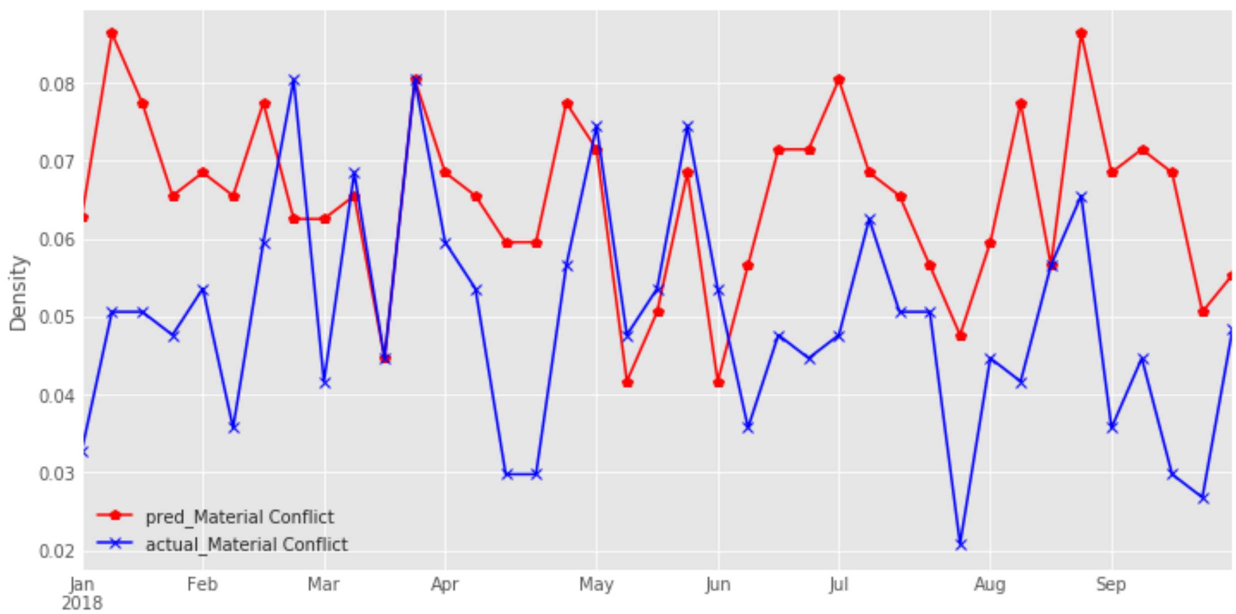

Figure 3. Observed versus Predicted Material Conflict Densities. Densities were computed for weekly time intervals. The model predicted the correct direction of the density trend in 71.79% of cases. The model performed particularly well from March to June 2018, months which witnessed a high frequency of political and civil conflicts surrounding gun violence (e.g., March for Our Lives, March 24th, 2018) and the Trump administration's "zero tolerance" policy (e.g., Families Belong Together, May -- June, 2018).

8. Discussion

This study examined how moral news frames and event occurrences are intertwined in a dynamic transactional process. First, we reviewed theoretical bridges linking production and societal outcomes of news frames (de Vreese, 2005). By building on this research, we introduced a macro-level perspective that situates motivationally-relevant news frames and event occurrences in a reciprocal influence cycle. Specifically, we highlighted the pervasive role of moral intuitions during both frame construction and framing effects (Tamborini, 2011), pointing to moral intuitions as promising integrative test bed to examine moral news frames as antecedent and consequence of events. Although empirical assessments between news frames and events have been stymied by a lack of suitable datasets, we highlighted the recently developed GDELT Interface for Communication Research (iCoRe; Hopp et al., 2019) as a promising pipeline to access large-scale archives of news frames and events. Furthermore, we pointed to the promise of Hidden Markov Models (HMM; Rabiner, 1989) as an integrative methodology for examining the non-linear, complex, and high-dimensional relationships between news and societal outcomes.

This work revealed two distinct findings: First, latent states characterized by a higher probability to observe conflict events (e.g., assaults and fights) and appeals were associated with a higher likelihood to observe moral news frames discussing human care and harm, whereas states with a higher probability to observe events referencing domestic and international cooperation were characterized by a higher likelihood to observe moral news frames pertaining to ingroup loyalty. These results emphasize that there are statistically-related, reciprocal interactions between moral news frames and events such that news coverage shapes and is influenced by particular event types, providing support for extant theoretical models of news-event transactions. Second we showed that HMMs can be utilized as a forecasting tool to predict future densities and trends in moral news frames and events based on previously observed news frame and event sequences. Focusing on the prediction of material conflict events, our HMM correctly predicted weekly trends in 71.79% of cases, outperforming various baseline models and performing similarly to previously reported conflict predictions (e.g., Petroff et al., 2013; Qiao et al., 2017).

These findings hint at the utility of HMMs for analyzing many of the dynamic and complex processes that permeate human communication (Street & Cappella, 1985). For example, media scholarship could benefit from a more thorough characterization of how certain sequential content patterns in media (e.g., reward and punishment structures in video games (Craighead, 2016)) relate to particular entertainment "states" (e.g., boredom versus flow (Huskey, Craighead, Miller, & Weber, 2018)). In online spaces, chains of visited news websites (Vermeer & Trilling, in press) may reveal latent patterns of news users' journeys. Furthermore, in interpersonal communication, researchers could have increased efficacy in investigating how sequences of dyadic (Cappella, 1979) and group interactions (DeDeo, 2016) reveal hidden, conversational states linked to mutual understanding and conflict, affective responses, personal closeness, or accommodation.

8.1. Limitations and Future Directions

This study has limitations that offer directions for future research. First, our herein utilized machine-coded event data should be complemented using large-scale, manually-verified event coding systems such as the Global Terrorism Database (LaFree & Dugan, 2007). Likewise, the herein employed bag-of-words, dictionary-based framing measures are constrained in their capacity to capture more nuanced, generic framing concepts such as "responsibility," "economic consequences," or "human interest" (e.g., Semetko & Valkenburg, 2000). Although the utilized Moral Foundations Dictionary (MFD; Graham et al., 2009) is a popular tool for identifying moral keywords in text, the MFD remains limited in detecting more intuitive, latent aspects of moral framing that may not be captured via manually pre-determined keywords. To overcome these limitations, a crowd-sourced, extended Moral Foundations Dictionary (eMFD; Hopp et al., 2019) has recently been developed and is currently being integrated into GDELT. Furthermore, dictionary-based approaches generally fail to capture agent-patient relationships (e.g., *who* interacts with *whom* and in *what* manner), and are equally limited in assessing framing patterns that are expressed across sequences of paragraphs. Hence, future work employing HMMs to assess dynamics between news frames and events should build on emerging work that extracts frames via more sophisticated techniques, including semantic network analysis (D'Angelo & Kuypers, 2010) and machine-learning (Burscher et al., 2016).

Second, future studies may investigate the feasibility of aggregating events and news frames (e.g., hourly, daily, or weekly levels) and thereby experiment with continuous representation of our event and news sequences. Likewise, we urge future research to compare the performance of HMMs to other time-series models. The discrete-valued time-series data employed herein cannot be readily analyzed with linear models (Priestley, 1988), as news frame and event sequences are not symmetric around 0, but instead bound by 0. This said, Qiao et al. (2017) have shown that HMMs outperform baselines and logistic regressions when predicting periods of social unrest in East Asia.

Third, this study took a massive-scale computational approach to examine the “statistical geometry” that captures the evolving relationships between news frames and events. While this approach facilitates a systems-level understanding of these processes, it does not readily afford an understanding of the micro-scale social and psychological processes that influence individual evaluations and behaviors. Future research may thus combine a macro-level approach such as the one used in this work, with micro-scale experimental paradigms to distill how the influence of frames on individuals give rise to large-scale, societal outcomes.

9. Concluding Remarks

This study examined the reciprocal relationships between news frames and event occurrences within the context of moral intuitions. Our application of Hidden Markov Models to analyse sequences of unfolding moral news frames and events provide empirical evidence for the conjecture that “the media shape and influence the course of events, and indeed, create events that would not have existed in their absence“ (Thompson, 1995, p.117). In doing so, this work serves to further demonstrate the utility of framing research for “bridg[ing] parts of the field that need to be in touch with each other” (Reese, 2007, p. 148). We anticipate that the theoretical synthesis and computational approach outlined herein will provide communication scholars a framework for more nuanced investigations of the complex transactional relationships between news coverage and newsworthy events.

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