Useful for our paper, similar ideas
• Appendix

Frames and their Affective Dimensions: A Case Study of Climate Change News Articles

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Abstract. News articles shared on social media platforms could be framed in ways such that specific points are emphasized or de-emphasized to create confusion on scientific facts. In this work, we use policy frames suggested by Boydstun et al., 2014 to find frames used in over 810k climate change news articles shared on Twitter by news agencies. Moreover, we present a method to find affective dimensions, namely Evaluation (good vs. bad), Potency (strong vs. weak), and Activity (active vs. passive), of the frames. Our results suggest that news articles about climate change are predominantly framed as related to policy issues in the context of a social group's traditions, customs, or values. We also conclude that frames are not reshared based on their *affect*. Lastly, we present implications for the increasingly relevant climate change communication research.

Keywords: Climate Change Communication · Framing · Affective Dimensions.

1 Introduction

One way to analyze how information is manipulated is by studying *frames* of the presented information, where framing presents certain information in a manner that emphasizes one issue over another. For example, news on Californian wildfires can be framed either as a natural event causing destruction of property or a human-made disaster causing socio-economic harm. More generally, framing is defined as "selecting certain aspects of a given issue and making them more salient in communication in order to 'frame' the issue in a specific way" [41].

Different approaches have been proposed in Natural Language Processing (NLP) / linguistics research to analyze frames. These approaches are broadly divided into formal/stylistic frames or content-oriented frame [41]. Formal/Stylistic frames concentrate on the structure or formal presentation of text rather than the content (e.g. Iyengar [27, 28]). Content oriented frames focus on the communicative text. Content-oriented frames can further be divided into generic frames or topical frames [11]. Topical frames are issue-specific. In NLP to analyze topical frames, we use computational models such as Latent Dirichlet Allocation

(LDA)[5], Latent Semantic Analysis (LSA) [23] and more recently transformer model techniques such as Top2Vec [2]. On the other hand, generic frames are pre-defined sets of categories or patterns that transcend individual issues. For example, Semetko and Valkenburg [44] used frames such as "consequences", "responsibility", "conflict", "human interest", and "morality" on press and television news on European politics. This paper discusses and develops methods to find generic frames on news articles on a crucial socio-economic topic, i.e., climate change.

Topical frames have been used in climate change contexts (e.g. [35] and [26]). However, content framing in articles related to climate change using generic framing techniques is mostly unexplored [41]. Hence, the first research question answered in the present work is, *Which generic frames are predominant in news articles related to climate change?* We answer this research question by using news articles shared on Twitter about climate change. To investigate generic frames in climate change news articles, we discuss and develop a framework to analyze generic frames in large data using a transfer learning approach. We use a pre-trained BERT [12] model to predict sentence level frames. For our analysis, we propose to use frames discussed in the Policy Frame Codebook [7] via a dataset annotated with these frames. The dataset is called Media Frame Corpus (MFC) [9], which is an annotated dataset of Wall Street Journal articles. The articles are annotated as per the Policy Frame Codebook's 15 frames [7] and are commonly used in multiple NLP framing analysis studies [14, 40].

Moreover, we develop a method to connect *Affect Control Theory (ACT)* with frames of news articles shared on a social network by news agencies. ACT, initially introduced by Heise [19, 20], proposes that individuals maintain their *affective* identities through their actions. The affective identities are operationalized by embedding these in Evaluation (good *vs.* bad), Potency (strong *vs.* weak), and Activity (active *vs.* passive) (EPA) space. We develop a method to embed frames in the EPA space, assuming that each frame has a particular affective meaning. Although prior work in NLP has identified ways to extract affective dimensions from pre-trained word embeddings (e.g. Field and Tsvetkov [15]), this paper discusses how we can embed and operationalize the affective dimensions of frames themselves. We then use our methodology on climate change news articles shared on Twitter[4].

Our approach of embedding the policy frames in the EPA dimension helps us determine news articles' emotional valence. In this work, we assume that a person or a news agency sharing the articles on social media with a certain frame would identify with that frame. Therefore, we discuss a mechanism where we can identify an article's emphasis (frame) in the EPA space. To the best of our knowledge, this is the first attempt at connecting computational generic framing research in NLP with ACT. By connecting frames with ACT, we draw implications for climate change communication. Hence, we find frames that are better at communicating climate change urgency as per emotional sociology. Thus, the second research question we address is, *what are the affective dimensions of the*

[4] In §7 we discuss examples of the framing and affect values of the dataset articles.

frames and which frames are more active and hence suited for communicating climate change urgency?

Once we have found the frames' affective dimensions, we use the reshare (retweet) count of each frame to find whether each frames' emotional value or *affect* leads to more reshare. ACT states that *affect* drives individual identities and their actions. In this work, we address, *whether or not the frames' affect drive the reshare count on social media?* To answer this research question, we use the reshare count of different frames. We hence conclude which frames in climate change news articles are more likely to be reshared.

We begin by providing an overview of the framing literature and ACT in §2. Next, we describe our data collection (§3.1), our methodology in §3.2, and our results in (§4). Through this research, we (1) compare different methods for framing analysis of articles using MFC, (2) develop a method to connect computational generic framing analysis with ACT, (3) show that frames with high *affect* do not necessarily drive news articles in climate change conversations on social media, and (4) present insights and implications for climate change communication framing.

2 Background and Related Work

2.1 Framing Analysis

In prior work, framing analysis is used to find bias or partisanship in news articles. Field et al. [14] use framing analysis to find media manipulation by the Russian government during economic downturns. Roy and Goldwasser [40] breaks down the policy frames [7] into more detailed sub-frames to demonstrate ideological differences between media sources. Johnson et al. [30] used weakly supervised approaches to predict frames used in political conversations on Twitter. Moreover, in a recent study, an annotation method is developed for social media framing analysis. Hartmann et al. [17] used multi-task and adversarial learning to annotate social media platforms' conversations. There has been work on predicting document and sentence level frames using MFC. Card et al. [10] predicted document level frames using a logistic regression model with latent dimensions and word-based features. This work was further improved by Ji and Smith [29], and Naderi and Hirst [37] used recurrent neural networks for sentence-level prediction of frames. In this work, we discuss BERT based novel techniques for sentence-level prediction of frames and show how framing analysis could be used in a social network setting. Apart from BERT based approaches, we use pretrained word embeddings to decontextualize MFC corpus and predict frames on a different topic.

2.2 Affect Control Theory (ACT)

As framed initially by Heise [18–20], ACT was developed to explain behavior in social interaction context. Specifically, *affect* refers "to any evaluative (positive or negative) orientation toward an object" [39]. In ACT, the *affective* dimensions (EPA dimensions) could describe a persona's reaction to various situations. Each dimension in EPA space lies on the continuous interval [-4.3,+4.3]. The first dimension is "Evaluation," which describes the identity in the goodness vs. badness dimension, where a negative value indicates an identity leaning more towards bad compared to good. Similarly, "Potency" describes strong vs. weak. Lastly, the "Activity" dimension describes the level of energy as active or passive. ACT theory states that it is the *affect* that we maintain during any interaction rather than a community assigned labels. For example, someone would try to maintain the affective meaning of a father ("quite good, very powerful, and somewhat lively" [39]) throughout their interactions. The affective meanings could change depending on the culture but are largely consistent. Social scientists codify ACT model by using a triplet of actor, behavior, and object. Each of the elements in the triplet is then measured in EPA space. In other words, each actor, behavior, and object would have an associated value in EPA space. Using the emotional signals the ACT lexicon gives, we embed the MFC frames in EPA space. This helps us understand users' perspectives while sharing the frame and connect it to wider emotional social science research.

Prior work related to ACT is rich and mostly out of scope for this paper. Therefore, we will touch upon the work which is relevant to this study. Joseph et al. [32] developed methods grounded in ACT to find affective stereotypes in Twitter users who tweeted about the Michael Brown and Eric Garner tragedies. Joseph et al. [31] used ACT to predict sentiments held towards entities or behavior using a large corpus of newspaper articles. More recently, Xiang et al. [49] used ACT lexicon to enhance the deep learning model for sentiment analysis.

3 Data and Method

3.1 Data

News Articles: We collected tweets using Twitter's standard API[5] with keywords "Climate Change", "#ActOnClimate", "#ClimateChange". The collection period was between August 26th, 2017 to January 4th, 2019. The collection was paused from April 7th, 2018 to May 21st, 2018, due to server errors. Hence, our results are not reflective of these periods. Our dataset consisted of 38M unique tweets and retweets from 11M unique users.

Next, we scrape all the articles shared by news agencies on Twitter using the collected tweets. To find out whether an account is from a news agency, we use a pre-trained model as described in Huang and Carley [24]. The model uses a long-short-term memory neural network [22] with an attention mechanism [4] trained on over 10,000 users. The test accuracy reported on a held-out dataset is 91.6%. We found $\sim$ 3% percent of users as news agency account with 1.1M unique tweets and retweets. For each of the tweets, we scraped the article shared via URL. We collected 900k files shared via URL. Out of these 900k files, we

[5] `https://developer.Twitter.com/en/docs/tweets/search/overview/standard`

removed the files which were non-text files and all the files with the error message returned from scraping the news outlet's website. After removing the unwanted files, we were left with 810k articles spread across the same timeframe as the Tweets dataset [6]. We will refer to these articles as *news articles* in this paper.

Media Frames Corpus: Work by Boydstun et al. [7], also referred to as Policy Frame Codebook, defines a list of frames that are commonly used in news articles. Media Frame Corpus [9], is an annotated dataset of 22,030 wall street journal articles. The articles are annotated as per the Policy Frame Codebook's 15 frames. The dataset consists of articles related to death penalty, gun control, immigration, samesex marriage, and tobacco. The annotation is done manually and could span one or more sentences. However, Media Frame Corpus does not cover climate change related annotated articles and is biased towards the Wall Street Journal's articles. Hence, we use decontextualization methods on the corpus as described in §3.2.

ACT Lexicon: We use the expanded EPA lexicon published by Heise [21]. The lexicon was obtained by manual annotation. We further expand the lexicon with Robinson et al. [38], Smith-Lovin et al. [45, 46] datasets, where each word has two different EPA scores; hence, we take the two scores' mean value. In the case of words appearing in multiple data sources with different EPA scores, we take the mean value of each dimension's scores.

3.2 Method

Frame Prediction We use the information score based classification technique as discussed in Field et al. [14] and propose other transformer-based classifiers for sentence-level prediction of frames. In this section, first, we discuss BERT-based models to predict frames at the sentence level. Second, we discuss information score based methods. Last, we evaluate these models for sentence-level accuracy scores. For evaluation, as a benchmark model, we use the Bi-LSTM model proposed by Naderi and Hirst [37].

BERT based models: We use a pretrained BERT model to get embeddings of the sentences of different MFC topics. Then we train (1) MLP with one hidden layer of dimension 512 and a softmax layer, (2) 1-D convolution neural network (1D-CNN) similar in dimension to Kim [34].

Information score based prediction: We use the information score based technique as used and validated in Field et al. [14]. In the study, each word is assigned an information score depending upon the frequency of that word occurring in a particular frame. Models evaluated are: (1) PMI-Non Decontextualize : Use information score of unigrams to predict each document's frame similar to Field et al. [14] but without extension of vocabulary, (2) Field et al. [14] : Use information scores but decontextualize by selecting similar words and assigning them the same score using pre-trained continuous bag of words (CBOW) language model embeddings, (3) PMI- Decontextualize (CBOW/FastText): We

[6] We further discuss our collection process, dataset statistics, frames, and BERT model parameters in §6.

use the information score lexicons, but instead of adding similar words, we find words during testing which are not in our information score vocabulary. Then we assign these words a score based on a pre-trained language model (CBOW or FastText [6]). The score is assigned for each missing word based on the nearest word in our information score vocabulary.

Evaluation: To check how well the learned models transfer, we train models on four topics and test the model on a different topic. We report the 15-class average prediction accuracy for sentence-level prediction task in Table 1. Pre-trained BERT models outperform other models. This shows the advantage of attention based models as shown by results reported for major NLP tasks in Devlin et al. [12]. For further analysis of frames we would rely on the validated PMI model [14] which gives reasonable accuracy and is much faster and hence practical to run on 810k articles. Moreover, in §4 we report a frame as dominant if the frame is in the top 3 of all the frames. The accuracy of this task increases to ∼80%.

Table 1. Prediction accuracy for sentence-level 15 class frame prediction. Given 5 topics in MFC, the accuracy values refer to the average accuracy of training on four topics and predicting on the other remaining topic. * Naderi and Hirst [37] used same topic for testing and training.

Model	**Accuracy**
BenchMark -BiLSTM	0.52*
BERT + MLP	0.53
BERT + CNN	0.54
PMI-Non Decontextualize	0.41
Field et al. [14]	0.47
PMI- Decontextualize (CBOW)	0.48
PMI- Decontextualize (FastText)	0.48

Frame Projection to EPA Field et al. [14] gives an information score to each word based on the word belonging to one frame over the other. We use the same method to find the information score for each word. Similar to Field et al. [14], Roy and Goldwasser [40], we remove all words occurring in 2% and 98% of the articles. We enriched our lexicon using the decontextualization method used in Field et al. [14] and as benchmarked above (model (2)) with other models. For each frame F, the information score for each word is defined as follows:

$$I(F, w) = \frac{P(F, w)}{P(F)P(w)} = \frac{P(w|F)}{P(w)} \tag{1}$$

where $P(w|F)$ is calculated from the fraction of count of words w and count of all words in sentences annotated with frame F. Similarly, $P(w)$ is calculated from entire MFC training data. We use symbol f to denote set of words with information score associated to frame F.

Next, we use the ACT lexicon (l) to get a $[E_{w'}, P_{w'}, A_{w'}]$ score for each word $w' \in l$. We define EPA score of each frame F as:

$$[E_F, P_F, A_F] = \sum_{c \in l \cap f} \frac{I_{(F,c)} * [E_c, P_c, A_c]}{Z} \tag{2}$$

where Z is the normalization factor equal to the number of words in both EPA lexicon (l) and f. In Equation 2 each word which is in both the lexicons are weighted by their respective information score in EPA space. We checked the densities of word score distributions ($I_{(F,c)} * [E_c, P_c, A_c]$) for each frame to find no multi modalities. Moreover, we conducted bootstrap sampling tests on the mean estimate of different frame's EPA scores obtained from Equation 2. We find that for all frames, the estimate becomes significant (p < 0.01) for $\#(c \in l \cap f) > 300$ words. In §6 Table 2 we report the number of common words in EPA lexicons (l) and different frames (f). We find that "Capacity and Resources" frame has the least number of common words with 1210 words and "Crime and Punishment" and "Cultural Identity" with the most common words with 1756 words each.

Frame's Average Reshare Count To find out the mean reshare count for each frame, we use each article's retweet count. For each of the 810k news articles shared via Tweets we scrape the retweet count using Twitter's standard API. We scraped the retweet count of each Tweet in January of 2021, assuming that this retweet count represents the final number of retweets. We believe that this assumption is reasonable since the last Tweet used to collect a news article was on January 4th, 2019 (refer §3.1). We use the retweet count and average information score calculated from the common words in framing lexicon (f) and each article to find the mean reshare count (R_F) of frame F as:

$$R_F = \frac{\sum_a r_a \frac{\sum_{c \in a \cap f} I_{(F,c)}}{\sum_F \sum_{c \in a \cap f} I_{(F,c)}}}{\#(a)} \tag{3}$$

Where r_a is the retweet count of each article a. In Equation 3, the numerator represents the weighted average of the retweet count for each frame given the information score of an article. This is then summed for each article. The denominator represents the total number of articles [7].

4 Results

4.1 Frame Prediction

We find that the "Cultural Identity" frame is the most dominant frame used in climate change articles. To find the frame of a document, we use all the sentence's average score in that document. In Figure 1 we report the count of the number

[7] Due to Tweet/user account deletion, we use 700k articles for our average reshare analysis.

of articles with respective dominant frames. We call a frame dominant if the frame is in the top 3 of all the frames. Apart from the "Cultural Identity" frame, we find that "Public Sentiment", "Political," and "Economic" frames are other considerable dominant frames. The "Cultural Identity" frame is defined as "traditions, customs, or values of a social group in relation to a policy issue" [7]. In a manual evaluation of a sample of 100 articles, we find that articles dominant in "Cultural Identity" framing are about changing current practices (eating habits, buying of estate etc.), about protests regarding climate change or changes after a natural disaster [8]. In Figure 1 we also report the average scores of the information scores used to calculate the dominant frame. There is a high correlation (Pearson Correlation = 0.9) between the top 3 dominant frames and the mean information scores. Frames such as "External Regulation and Reputation" and "Policy Prescription and Evaluation" show the opposite behavior. We conclude that these frames do occur regularly in different climate change articles but are more salient.

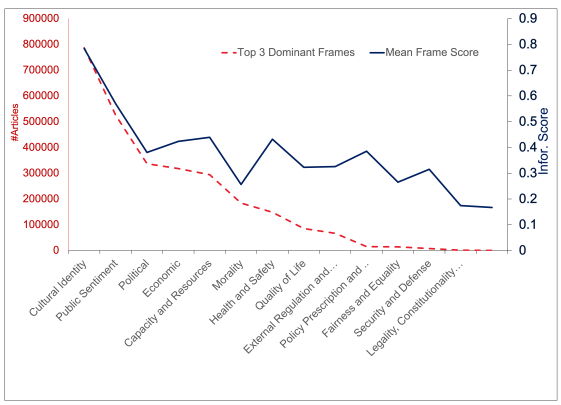

Fig. 1. Number of articles with corresponding top 3 frames and mean of the information score (Equation 1) for all the articles (blue).

4.2 Frames in EPA

We project the frames in EPA space to find that "Capacity and Resources", "Quality of Life," and "Morality" score high in the Evaluation (good vs. bad) dimension. "Morality" also scores high in Potency (strong vs. weak). In Figure 2, we report each frame's EPA dimension and the centered and scaled value to better show contrast between frames. On a manual inspection of top words contributing to high Potency values of "Morality" frame, we find words related to religion such as *jesus*, *christ* and *church*. These words have a higher than

[8] We discuss the details of the manual evaluation process in §7.

usual Potency value. “External Regulation and Reputation” and “Quality of Life” frame score high in the Activity (active vs. passive) dimension. Overall, we find that all the frames are positive (leaning good, strong, and active) with little variation. This is expected as frames are nuanced changes in the presentation of a topic. Moreover, the common words between the EPA lexicon and the frames represent news agencies' neutral emotions. We infer that the highly emotional words in the EPA lexicon are rare or do not occur in our framing information score lexicon.

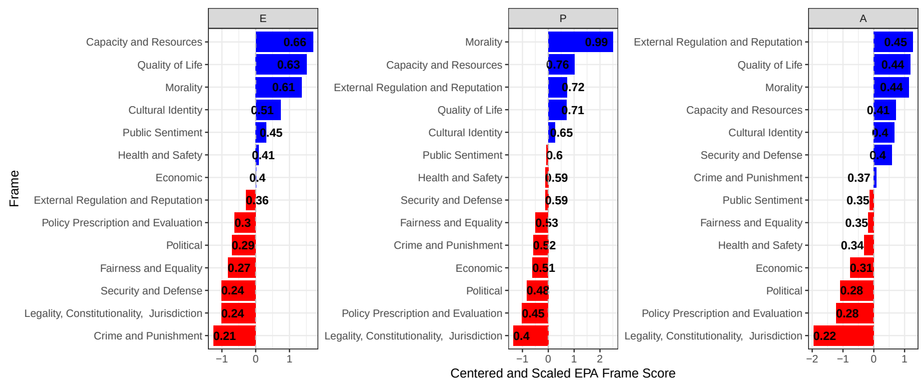

Fig. 2. EPA values centered by mean frame score and scaled by the standard deviation values of frames in each dimension. EPA scores of frames calculated using Equation 2 are in boldface. EPA dimension range is [-4.3,+4.3].

The EPA dimensions of frames used in news articles do not vary greatly with time. Figure 3 reports our results. For this analysis, we aggregate articles by month to find the average information score for each frame and then convert to the EPA dimension by taking a weighted average using the base EPA dimension score of each frame from Equation 2. Although the number of articles in each month varies greatly, we find little or no variation with time in all three affective dimensions. Potency dimension score is the highest, followed by Evaluation and then Activity. This is explained by the fact that in figure 2, each frame's base score is higher for the Potency dimension.

4.3 Reshare Count of Frames

The average reshare (retweet) count varies considerably for different frames. Figure 4 reports the average reshare count of each frame. The average reshare is less than 1, indicating that a high percentage of articles were not shared. In fact, only 35% of the news articles were shared more than once. We scrape articles from all accounts that exhibit news agency like behavior based on Tweets and user account's metadata. Based on our previous experiments using the classification

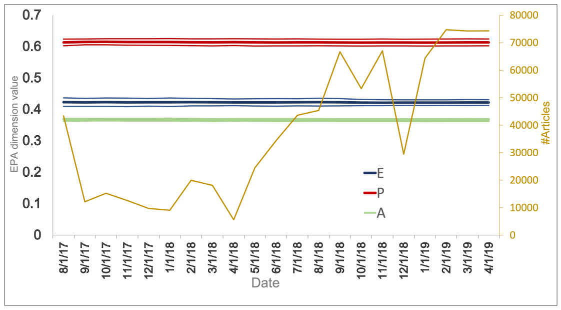

Fig. 3. EPA dimensions of frames used in climate change news articles aggregated by month and the total number of articles in each month. Extra lines of the corresponding color represent 1 standard deviation.

model, we infer that not many users follow a high percentage of the accounts labeled as news agency accounts. We suspect that some of these accounts could be bot-like. We leave the extended analysis for bot-like accounts for future work. On average, the "Cultural Identity" and "Public sentiment" frame is more than two times more reshared than the "Crime and Punishment" frame.

Next, we find out if *affect* of the frames drive their reshare activity. In figure 5, we report the emotional value of a frame by calculating the distance from the center (origin) of each frame in EPA dimensions. We find that "Morality", "Quality of Life" and "Capacity and Resources" frames are the most emotional, and "Legality, Constitutionality, Jurisdiction" is the least emotional frame. These results are generally consistent with common perceptions about these frames. We find that there is low correlation (Pearson Correlation = 0.15) between the emotional value of the frames and the average reshare count. This indicates that more emotional (higher *affect*) frames are not necessarily reshared more times.

5 Discussion

Emphasizing and de-emphasizing certain information to manipulate public opinion has led to a growing interest in learning automated frames in articles [40]. Moreover, work done by Kause et al. [33] indicates that difference in the framing of climate change communication could contribute to polarization in beliefs. In this work, we use MFC to find automated frames in an extensive corpus of climate change-related articles. We find that most of the articles on climate change are framed using mainly "cultural identity", "public sentiment", "political," and "economic" frames. In work done by Field et al. [14] related to the articles published by the Russian government news media were mostly "External Regulation", "Political" and "Morality" dominant while using keywords related to the U.S. In a similar work, Roy and Goldwasser [40] also classified news media articles and found the ideological differences in different news media presentation of similar topics. Given our corpus's extensive size, we believe the dominant

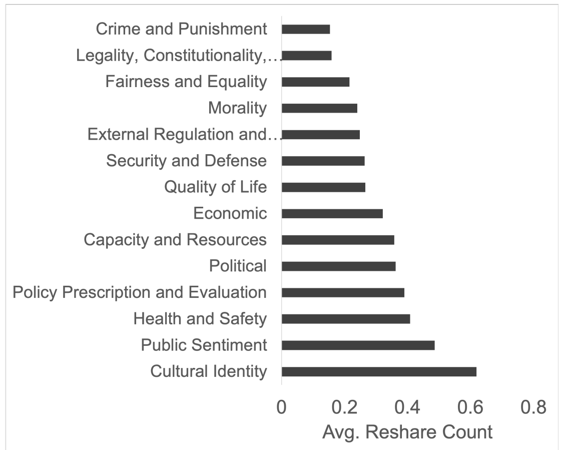

Fig. 4. Average reshare count (R_F) of each frame calculated using Equation 3.

frame in climate change articles reflects general news articles' nature shared on Twitter. In a manual analysis of 100 articles, we find that news articles about climate change predominantly discuss topics involving changing habits, protests, and the effects of natural disasters. Moreover, the 100 random articles used in our manual evaluation were, for the most part, from local or non-popular news sources. Thus, these news articles either address the population of a specific place or a region or are reposts of national/international news stories.

A perception exists in climate change communication that "considerable competition among (and between) scientists, industry, policymakers and non-governmental organizations (NGOs), each of whom is likely to be actively seeking to establish their particular perspectives on the issues" [1]. Previous studies have described climate change framing in "scientific uncertainty" frame [13, 36]. This framing has recently changed to "industry leadership" frame in defeating climate change [25]. Frames have also been shown to differ between countries and over time [16, 42, 43]. A recent work done by Badullovich et al. [3] suggests that scientific literature on climate change most commonly use "Scientific, Economic and Environmental" frames and are increasingly using "Public health, Disaster, and Morality/ethics" frames. In our study, instead of focusing on manual analysis, we use computational models to build on climate change communication's rich framing research. Moreover, we focus on news media to decipher perspectives as the media plays a vital role in climate change communication. Using the retweet count of each article shared via Twitter, we calculated the average number of times a frame is reshared. In this work, we show that certain frames are more reshared than others. Moreover, this resharing pattern is not correlated to different frame's emotional valence. This suggests that news stories are reshared based on other factors such as news media popularity, story type, and novelty. We recognize that the online data collected used English language

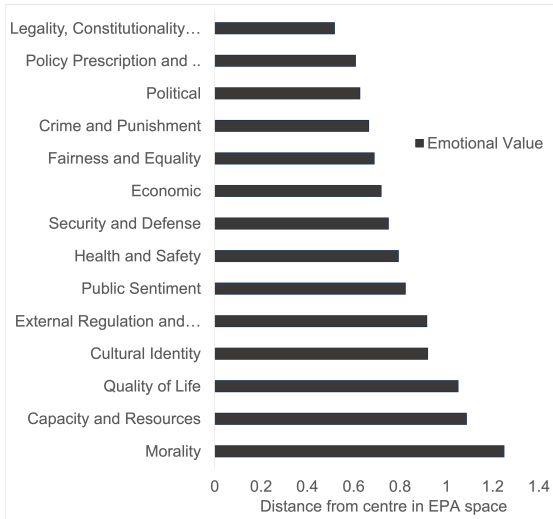

Fig. 5. Total emotional value of frames calculated by finding the distance from the origin (always >0) of the projected frames in EPA dimensions. A higher value signifies more emotions or *affect* for that frame.

keywords and did not reflect the demographic representativeness necessary to present cross-cultural conclusions.

In this paper, we develop a methodology to project frames in EPA space. We constructed a mechanism where the nuances of the article content are projected to EPA space. We do not make an effort to predict where articles themselves lie in EPA space. By projecting the frames into EPA space, we can now connect the same topic to emotional science research useful for studying group influence and belief change. Work done by Britt and Heise [8] gave clues that more active emotions could be used to incite minority groups by motivating them to participate in more extensive group activities. Our results indicate that frames such as "external regulation", "Quality of Life" and "morality" are more emotionally active (higher activity). As climate change action becomes more urgent and necessary, a more consistent and active framing should be used to convey the policy changes needed. Moreover, multiple previous research studies on climate change discussion on social media have concluded that different belief groups exhibit "echo-chamber" type behavior [47, 48]. These different belief groups can be analyzed to find their news sources and align messages with frames that are more likely to be shared by different belief groups.

Bibliography

[1] Anderson, A.: Media, politics and climate change: Towards a new research agenda. Sociology compass **3**(2), 166–182 (2009)

[2] Angelov, D.: Top2vec: Distributed representations of topics. arXiv preprint arXiv:2008.09470 (2020)

[3] Badullovich, N., Grant, W., Colvin, R.: Framing climate change for effective communication: a systematic map. Environmental Research Letters **15**(12), 123002 (2020)

[4] Bahdanau, D., Cho, K., Bengio, Y.: Neural machine translation by jointly learning to align and translate (Jan 2015), 3rd International Conference on Learning Representations, ICLR 2015 ; Conference date: 07-05-2015 Through 09-05-2015

[5] Blei, D.M., Ng, A.Y., Jordan, M.I.: Latent dirichlet allocation. Journal of machine Learning research **3**(Jan), 993–1022 (2003)

[6] Bojanowski, P., Grave, E., Joulin, A., Mikolov, T.: Enriching word vectors with subword information. Transactions of the Association for Computational Linguistics **5**, 135–146 (2017), URL `https://www.aclweb.org/anthology/Q17-1010`

[7] Boydstun, A.E., Card, D., Gross, J., Resnick, P., A. Smith, N.: Tracking the development of media frames within and across policy issues (Jun 2018), https://doi.org/10.1184/R1/6473780.v1, URL `https://kilthub.cmu.edu/articles/journal_contribution/Tracking_the_Development_of_Media_Frames_within_and_across_Policy_Issues/6473780/1`

[8] Britt, L., Heise, D.: From shame to pride in identity politics. Self, identity, and social movements **5**, 252–68 (2000)

[9] Card, D., Boydstun, A., Gross, J.H., Resnik, P., Smith, N.A.: The media frames corpus: Annotations of frames across issues. In: Proceedings of the 53rd Annual Meeting of the Association for Computational Linguistics and the 7th International Joint Conference on Natural Language Processing (Volume 2: Short Papers), pp. 438–444 (2015)

[10] Card, D., Gross, J., Boydstun, A., Smith, N.A.: Analyzing framing through the casts of characters in the news. In: Proceedings of the 2016 Conference on Empirical Methods in Natural Language Processing, pp. 1410–1420, Association for Computational Linguistics, Austin, Texas (Nov 2016), https://doi.org/10.18653/v1/D16-1148, URL `https://www.aclweb.org/anthology/D16-1148`

[11] De Vreese, C.H.: News framing: Theory and typology. Information design journal & document design **13**(1) (2005)

[12] Devlin, J., Chang, M.W., Lee, K., Toutanova, K.: BERT: Pre-training of deep bidirectional transformers for language understanding. In: Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers), pp. 4171–4186, Association for Computational Linguistics, Minneapolis, Minnesota (Jun 2019), https://doi.org/10.18653/v1/N19-1423, URL `https://www.aclweb.org/anthology/N19-1423`

[13] Dunlap, R.E., McCright, A.M.: Organized climate change denial. The Oxford handbook of climate change and society **1**, 144–160 (2011)

[14] Field, A., Kliger, D., Wintner, S., Pan, J., Jurafsky, D., Tsvetkov, Y.: Framing and agenda-setting in Russian news: a computational analysis of intricate po-

litical strategies. In: Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing, pp. 3570–3580, Association for Computational Linguistics, Brussels, Belgium (Oct-Nov 2018), https://doi.org/10.18653/v1/D18-1393, URL `https://www.aclweb.org/anthology/D18-1393`

[15] Field, A., Tsvetkov, Y.: Entity-centric contextual affective analysis. In: Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics, pp. 2550–2560, Association for Computational Linguistics, Florence, Italy (Jul 2019), https://doi.org/10.18653/v1/P19-1243, URL `https://www.aclweb.org/anthology/P19-1243`

[16] Gupta, J.: A history of international climate change policy. Wiley Interdisciplinary Reviews: Climate Change **1**(5), 636–653 (2010)

[17] Hartmann, M., Jansen, T., Augenstein, I., Søgaard, A.: Issue framing in online discussion fora. In: Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers), pp. 1401–1407, Association for Computational Linguistics, Minneapolis, Minnesota (Jun 2019), https://doi.org/10.18653/v1/N19-1142, URL `https://www.aclweb.org/anthology/N19-1142`

[18] Heise, D.R.: Understanding events: Affect and the construction of social action. CUP Archive (1979)

[19] Heise, D.R.: Affect control theory: Concepts and model. Journal of Mathematical Sociology **13**(1-2), 1–33 (1987)

[20] Heise, D.R.: Expressive order: Confirming sentiments in social actions. Springer Science & Business Media (2007)

[21] Heise, D.R.: Surveying cultures: Discovering shared conceptions and sentiments. John Wiley & Sons (2010)

[22] Hochreiter, S., Schmidhuber, J.: Long short-term memory. Neural computation **9**(8), 1735–1780 (1997)

[23] Hofmann, T.: Probabilistic latent semantic indexing. In: Proceedings of the 22nd annual international ACM SIGIR conference on Research and development in information retrieval, pp. 50–57 (1999)

[24] Huang, B., Carley, K.M.: Discover your social identity from what you tweet: a content based approach. Disinformation, Misinformation, and Fake News in Social Media - Emerging Research Challenges and Opportunities (2020)

[25] Ihlen, Ø.: Business and climate change: the climate response of the world's 30 largest corporations. Environmental Communication **3**(2), 244–262 (2009)

[26] Ivanova, A.: Transnationalisierung von Öffentlichkeiten. Springer (2017)

[27] Iyengar, S.: Is anyone responsible?: How television frames political issues. University of Chicago Press (1994)

[28] Iyengar, S.: Framing responsibility for political issues. The Annals of the American Academy of Political and Social Science **546**(1), 59–70 (1996)

[29] Ji, Y., Smith, N.A.: Neural discourse structure for text categorization. In: Proceedings of the 55th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), pp. 996–1005, Association for Computational Linguistics, Vancouver, Canada (Jul 2017), https://doi.org/10.18653/v1/P17-1092, URL `https://www.aclweb.org/anthology/P17-1092`

[30] Johnson, K., Jin, D., Goldwasser, D.: Leveraging behavioral and social information for weakly supervised collective classification of political discourse on Twitter. In: Proceedings of the 55th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), pp. 741–752, Association for Computational

Linguistics, Vancouver, Canada (Jul 2017), https://doi.org/10.18653/v1/P17-1069, URL `https://www.aclweb.org/anthology/P17-1069`

[31] Joseph, K., Wei, W., Benigni, M., Carley, K.M.: A social-event based approach to sentiment analysis of identities and behaviors in text. The Journal of Mathematical Sociology **40**(3), 137–166 (2016)

[32] Joseph, K., Wei, W., Carley, K.M.: Girls rule, boys drool: Extracting semantic and affective stereotypes from twitter. In: Proceedings of the 2017 ACM Conference on Computer Supported Cooperative Work and Social Computing, pp. 1362–1374 (2017)

[33] Kause, A., Townsend, T., Gaissmaier, W.: Framing climate uncertainty: Frame choices reveal and influence climate change beliefs. Weather, Climate, and Society **11**(1), 199–215 (2019)

[34] Kim, Y.: Convolutional neural networks for sentence classification. In: Proceedings of the 2014 Conference on Empirical Methods in Natural Language Processing (EMNLP), pp. 1746–1751, Association for Computational Linguistics, Doha, Qatar (Oct 2014), https://doi.org/10.3115/v1/D14-1181, URL `https://www.aclweb.org/anthology/D14-1181`

[35] Kirilenko, A.P., Stepchenkova, S.O.: Climate change discourse in mass media: application of computer-assisted content analysis. Journal of Environmental Studies and Sciences **2**(2), 178–191 (2012)

[36] McCright, A.M., Dunlap, R.E.: Defeating kyoto: The conservative movement's impact on us climate change policy. Social problems **50**(3), 348–373 (2003)

[37] Naderi, N., Hirst, G.: Classifying frames at the sentence level in news articles. Policy **9**, 4–233 (2017)

[38] Robinson, D.T., Smith-Lovin, L., Cannon, B.C., Clark, J.K., Freeland, R., Morgan, J.H., Rogers, K.B.: Mean affective ratings of 932 identities, 810 behaviors, and 660 modifiers by university of georgia undergraduates in 2012-2014. University of Georgia: Distributed at UGA Affect Control Theory Website (2016), URL `http://research.franklin.uga.edu/act/`

[39] Robinson, D.T., Smith-Lovin, L., Wisecup, A.K.: Affect Control Theory, pp. 179–202. Springer US, Boston, MA (2006), ISBN 978-0-387-30715-2, URL `https://doi.org/10.1007/978-0-387-30715-2_9`

[40] Roy, S., Goldwasser, D.: Weakly supervised learning of nuanced frames for analyzing polarization in news media. In: Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP), pp. 7698–7716, Association for Computational Linguistics, Online (Nov 2020), https://doi.org/10.18653/v1/2020.emnlp-main.620, URL `https://www.aclweb.org/anthology/2020.emnlp-main.620`

[41] Schäfer, M.S., O'Neill, S., Nisbet, M., Ho, S., Markowitz, E., Thaker, J.: Frame analysis in climate change communication: approaches for assessing journalists' minds, online communication and media portrayals. Oxford Research Encyclopedia of Climate Science (2017)

[42] Schlichting, I.: Strategic framing of climate change by industry actors: A meta-analysis. Environmental Communication: A Journal of Nature and Culture **7**(4), 493–511 (2013)

[43] Schmidt, A., Ivanova, A., Schäfer, M.S.: Media attention for climate change around the world: A comparative analysis of newspaper coverage in 27 countries. Global Environmental Change **23**(5), 1233–1248 (2013)

[44] Semetko, H.A., Valkenburg, P.M.: Framing european politics: A content analysis of press and television news. Journal of communication **50**(2), 93–109 (2000)

[45] Smith-Lovin, L., Robinson, D.T., Cannon, B.C., Clark, J.K., Freeland, R., Morgan, J.H., Rogers, K.B.: Mean affective ratings of 929 identities, 814 behaviors, and 660 modifiers by university of georgia and duke university undergraduates and by community members in durham, nc, in 2012-2014. University of Georgia: Distributed at UGA Affect Control Theory Website (2016), URL `http://research.franklin.uga.edu/act/`

[46] Smith-Lovin, L., Robinson, D.T., Cannon, B.C., Curdy, B.H., Morgan, J.H.: Mean affective ratings of 968 identities, 853 behaviors, and 660 modifiers by amazon mechanical turk workers in 2015. University of Georgia: Distributed at UGA Affect Control Theory Website (2019), URL `http://research.franklin.uga.edu/act/`

[47] Tyagi, A., Babcock, M., Carley, K.M., Sicker, D.C.: Polarizing tweets on climate change. In: International Conference on Social Computing, Behavioral-Cultural Modeling and Prediction and Behavior Representation in Modeling and Simulation, pp. 107–117, Springer (2020)

[48] Williams, H.T., McMurray, J.R., Kurz, T., Lambert, F.H.: Network analysis reveals open forums and echo chambers in social media discussions of climate change. Global environmental change **32**, 126–138 (2015)

[49] Xiang, R., Long, Y., Wan, M., Gu, J., Lu, Q., Huang, C.R.: Affection driven neural networks for sentiment analysis. In: Proceedings of the 12th Language Resources and Evaluation Conference, pp. 112–119, European Language Resources Association, Marseille, France (May 2020), ISBN 979-10-95546-34-4, URL `https://www.aclweb.org/anthology/2020.lrec-1.14`

6 Appendix 1

Definition of framing dimensions from Boydstun et al. [7]:

- Economic: costs, benefits, or other financial implications
- Capacity and resources: availability of physical, human or financial resources, and capacity of current systems
- Morality: religious or ethical implications
- Fairness and equality: balance or distribution of rights, responsibilities, and resources
- Legality, constitutionality and jurisprudence: rights, freedoms, and authority of individuals, corporations, and government
- Policy prescription and evaluation: discussion of specific policies aimed at addressing problems
- Crime and punishment: effectiveness and implications of laws and their enforcement
- Security and defense: threats to welfare of the individual, community, or nation
- Health and safety: health care, sanitation, public safety
- Quality of life: threats and opportunities for the individual's wealth, happiness, and well-being
- Cultural identity: traditions, customs, or values of a social group in relation to a policy issue
- Public opinion: attitudes and opinions of the general public, including polling and demographics
- Political: considerations related to politics and politicians, including lobbying, elections, and attempts to sway voters

- External regulation and reputation: international reputation or foreign policy of the U.S.
- Other: any coherent group of frames not covered by the above categories

Table 2. Total number of common words in each frame lexicon f and EPA lexicon l.

Frame	**Total Common Words**
Capacity and Resources	1210
Crime and Punishment	1756
Cultural Identity	1756
Economic	1690
External Regulation and Reputation	1312
Fairness and Equality	1590
Health and Safety	1712
Legality, Constitutionality, Jurisdiction	1779
Morality	1631
Policy Prescription and Evaluation	1747
Political	1768
Public Sentiment	1685
Quality of Life	1720
Security and Defense	1519

6.1 Data Collection Details

As described in §3.1, we collected Tweets using Twitter's standard API [9] using keywords "Climate Change", "#ActOnClimate", "#ClimateChange". Table 3 reports statistics of the dataset. We then classify each user into a news agency account and a non-news agency account using the method described in §3.1. For each Tweet from a news agency account, we scrape the *news article* using the URL shared in that Tweet. To scrape the news articles, we built our software system, which uses python *requests* library to scrape the articles from the websites. We subscribed to news agencies mentioned in Pew Research's top online news media websites report [10] as these websites generally required login credentials. Extensive testing was done to ensure that we could collect as many articles as possible and circumvent possible obstacles such as AJAX calls and advertisements. Using the URLs we were able to collect 900k articles. However, some of these articles were non-text files or contained short error messages. We

[9] `https://developer.twitter.com/en/docs/twitter-api/v1/tweets/search/overview`

[10] `https://www.pewresearch.org/wp-content/uploads/sites/8/legacy/NIELSEN-STUDY-Copy.pdf`

removed these files from our dataset. After this step, we were left with 810k news articles. In table 3 we report statistics of news articles used in our dataset. We further cleaned each article for any HTML tags, other non-header, or non-body text for our analysis.

6.2 Bert Model Details

For predicting frames at the sentence level, we use the pretrained Bert-Large-Uncased model. As per Devlin et al. [12] the model has 24-layer with 1024 hidden dimension, 16 attention heads, and 336 M parameters. The model was trained on BookCorpus [11] and English Wikipedia after removing headers, tables, and lists. In this work, we predict frames for news articles, assuming that the formal language used in books and Wikipedia generally reflects the language used in news articles. To get embedding of a sentence we concatenate the last 4 layers of the BERT model, as suggested in Devlin et al. [12]. This embedding was then passed to a MLP/1D-CNN classifier as described in §3.2.

Table 3. Statistics of the Tweets and news articles collected as described in §3.1.

	Tweets	**Articles**
Total Number	38M	810k
Mean per day	48,860.5	1,157.5
Min per day	2	0
Max per day	243,574	6,513

7 Appendix 2

In this section, first, we will give some examples from our news articles dataset. Second, we use these examples to explain the frames and their projection in EPA space. Lastly, we discuss the methodology and results of our manual evaluation of 100 randomly selected news articles.

Snippets of news articles in our dataset:

Snippet (a): *"STUDY REVEALS HOW CLIMATE CHANGE COULD CAUSE GLOBAL BEER SHORTAGES Severe climate events could cause shortages in the global beer supply, according to new research involving the University of East Anglia (UEA). The study warns that increasingly widespread and severe drought and heat may cause substantial decreases in barley yields worldwide, affecting the supply used to make beer, and ultimately resulting in "dramatic" falls in beer consumption and rises in beer prices."*

Snippet (b): *"Baltimore Is Suing Big Oil Over Climate Change The Supreme Court heard arguments this week in a case brought by the city of Baltimore against more than a dozen major oil and gas companies including BP, ExxonMobil and Shell. The city government argued that the fossil fuel giants must pay for the costs of climate change because they knew that their products cause potentially catastrophic global warming.*

[11] `https://yknzhu.wixsite.com/mbweb`

Snippet (c): *Small islands use big platform to warn of climate change On the map, their homes are tiny specks in a vast sea of blue, rarely in the headlines and far removed from the centers of power. But for a few days each year, the leaders of small island nations share a podium with presidents and prime ministers from the world's most powerful nations, and their message is clear: Global warming is already changing our lives, and it will change yours too. Speaking shortly after U.S. President Donald Trump — whose fiery speech made no mention of climate change — Danny Faure told the U.N. General Assembly this week that for his country, the Seychelles, it's already a daily reality.*

The snippets from the dataset show different frames used in climate change news articles. The topic discussed in these snippets is different; moreover, these snippets are addressed towards geographically different audiences. Snippet (a) addresses the change in a decrease in yield for barley due to climate change referencing a research study. This whole news article predominantly uses "Cultural Identity" frame. Similarly, the article in snippet (b) uses more "economic" and "Legality, constitutionality and jurisprudence" frame. The article from which Snippet (c) was taken is predominantly using "Quality of life", "Capacity and Resources" and "Morality" frames. Our algorithm discussed in §4.2 predicts that the article of snippet (c) is high in emotional value or *affect* followed by the article of snippet (b) and then by the article of snippet (a). This order can also be followed by looking at the predominant frames of these articles.

In order to find out the general stories reported in news articles, we manually verify stories of a sample of 100 news articles from our dataset. Moreover, we also find that if the news article is from a popular news agency or not. We mark the source as popular if its name is mentioned in Pew Research's top online news media websites report.

Two annotators independently annotated each news article to be related to: protests, natural disasters, social practices (such as drinking, eating, festivals, sports etc.), economic, policy or legal, flora and fauna, political, historical facts/data, satire on climate change action/lack of action, new scientific finding and, any other. We recognize these topics do not constitute all possible topics in the context of climate change. Using these groups, we were able to generalize the dominant stories in the climate change discussion to explain the dominant frames.

We find that social practices (15/13), protests (10/12) and, natural disaster-related (9/10) stories are most prominent. The "any other" (11/8) category was also prominent. The least prominent stories were in satire (1/4) and historical facts (2/2) group. The values in the bracket represent the number of stories as marked by each annotator. The % agreement between annotators is relatively high at 77%. A thorough topical analysis of a large sample of news articles would give a more robust insight into the dynamics of frames in climate change news articles. Future work could further the NLP frames research by connecting generic and topical frames/topics in large datasets. We also find that only 2 news articles are from popular news agencies as listed by Pew Research.