Climate Conversations Final Report

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Abstract

This project addresses the critical challenge of bridging the gap between complex scientific findings and public opinion on climate change, aiming to assist policymakers in crafting informed, society-benefiting policies. By harnessing data from Reddit's climate change discussions and academic journals, the research introduces a toolkit designed to align policymaker communication with constituents' concerns and scientific evidence. Utilizing topic modeling on Reddit discourse, the project identifies ten prominent themes, integrating moral foundations theory to tailor messaging that resonates with diverse constituents. Additionally, it employs abstractive and extractive summarization of scientific articles, providing policymakers with concise, scientific summaries relevant to each identified topic. This approach enables a nuanced understanding of public discourse and scientific consensus on climate change, offering a strategic foundation for effective policy communication. The study's integration of NLP techniques with moral foundations analysis presents a novel methodology for addressing the communicative challenges faced by policymakers in the context of climate change, demonstrating the potential for advanced computational tools to enhance public policy formulation and communication strategies.

Introduction

Policymakers are often tasked with the difficult challenge of integrating complex scientific findings (in areas where they may not be experts) with diverse and multifaceted public opinions to formulate policies that benefit society. This is particularly pronounced in the context of climate change, a pressing global issue that necessitates informed and widely supported policy interventions across multiple levels of government. This project seeks to bridge that communication gap more seamlessly by creating a toolkit that policymakers can use to address the various concerns of their constituents with relevant and accurate scientific information regarding climate change.

Our work primarily creates this toolkit drawing on information from two sources: (1) an analysis of online conversations about climate issues using data from Reddit posts and comments, and (2) scientific information from academic journals. Topic modeling of Reddit climate conversations is used to create ten topic-related toolkits, tying together guiding moral principles associated with each topic, called moral foundations. Moral foundation profiles are provided in the toolkit to guide how policymakers might frame their messaging to different types of constituents, while topics of interest are used to collect summaries of scientific articles that align with group interests. These journals are briefly summarized using two summarization techniques to provide the policymaker with the scientific backing to speak on any of these points to their electorate.

Work Completed

<u>Data Collection</u>

Nearly 10,000 academic journals were collected from ProQuest using TDMStudio's AWS tool to make up the dataset on which the HuggingFace abstractive summary was fine-tuned. This process required partitioning journal collection between multiple accounts to remain below TDMStudio's 30MB weekly download limit. Articles were collected from well-respected scientific journals in the fields of environmental science, green technology, and environmental policy based on their availability on the ProQuest database and high impact scores. We limited data to articles published after 2022 to retain scientific relevance and chose journals with impact scores greater than 1 to increase article quality and relevance. Ultimately, only around 3,000 of the collected articles were determined to contain full article text, which influenced the decision to fine-tune the abstractive summarization model on only abstracts and implement the extractive summarization model.

Nearly 4 million comments and 55,000 submissions were collected from a repository of Reddit data. We collected comments and submissions from eight subreddits that a literature search about researching climate change using Reddit data suggested would be useful for studying discussions of climate change on Reddit (Parsa et al., 2022; Treen et al., 2022). The subreddits we collected specific to climate change were r/climate, r/environment, r/climatechange, r/climateskeptics, and r/climateOffensive. Due to Parsa et al., 2022 and other sources noting that a lot of climate change discussions happen on subreddits that aren't specific to climate change, we also pulled comments and submissions from three of the most popular subreddits that contain a lot of discussion of climate change, which are r/science, r/politics, and r/worldnews. In order to improve our chances of seeing discussions of climate change within these three broader subreddits, we sampled our data from the vicinity of a major climate event, Hurricane Ian in 2022. We sampled from the eight above subreddits over the two weeks prior to Hurricane Ian, the one week when Hurricane Ian was making landfall, and the two weeks after Hurricane Ian so that we could compare across these three time periods. In total, data from these 8 subreddits over this 5-week period totaled about 4 million comments and 55,000 submissions.

<u>Article Summarization</u>

Machine Learning Implementations of Article Summarization

"SAPGraph: Structure-aware Extractive Summarization for Scientific Papers with Heterogeneous Graph" by Qi et. al. outlines a novel method of summarizing scientific papers. Scientific research papers pose a challenge to natural language processing models because of their unique structure and length. Previous models' summaries favor information written near the beginning of the paper over information written near the end. The SAPGraph approach employs an extractive GNN summarization method which takes the standard structure of scientific papers into account in its summarization to avoid this problem.

Using this method, paper sections are analyzed using subgraphs, and then connected based on the inherent section structure of scientific papers. The proportional space in this extractive summary given to each paper section is based on the number of sentences in each section scoring highly in relevance to the author summary. All sentences scored using and chosen for inclusion in the summary based on that score, assuming there is no trigram overlap with existing summary sentences. Final model performance is assessed with a ROUGE score.

Methodology 1: Article Text to Abstract Summarization using Article Sections, Cosine Similarity, Sentence Order, and LSTMs

We originally attempted to adapt the full SAPGraph model using the GitHub repository that Qi et al. provided to replicate their article findings. However, in attempting this, we saw that many of the files needed to implement the SAPGraph architecture, including the files necessary for preprocessing the data and information on when to use different aspects of the architecture, were not illuminated on. Our attempt to adapt their structure can be found in our ArticleSummarizer class.

Instead, we decided to loosely adapt Qi et al.'s method by replicating the way they used article sections as a way to build out their models. Specifically, we pulled the Introduction, Methods, Results, and Conclusion sections from each article, compared the sentences within each section to the article's abstract to develop targets, and built four separate LSTM models for predicting the importance of sentences for their relative sections. From there, we were able to build a summary using the most important sentences from each of the four sections. Further implementation details are below.

1. *Extracting Article Sections*

We began by extracting the Introduction, Methods, Results, and Conclusion sections from research articles. To do so, we first dropped from our full dataset any articles that did not have both the full article text and the abstract. This resulted in around 3,000 articles to use for the development of our model. We created a mapping of common header names and their most likely category; for example, we classified headers such as "Methodology" and "Materials and Methods" into the "Methods" category. Those headers that did not fit into the four categories–"Author's Contribution," "References," etc.--were initially classified into an "Other" category and eventually discarded before model-building took place. With the mapping of headers to categories, we used regex to identify where keywords were within a given article's text and section off each category's text into their own lists. Given our goal of creating a model per section, we created a dictionary aimed at saving the relevant text for each section. From there, we iterated through a given section's text and created a list of lists, where each outer list element represented an article, and each inner list element represented a tokenized sentence from that section. We used nltk's sentence tokenizer to achieve this tokenization.

2. *Identifying Sentence-level Targets*

The goal of our model was to identify sentences within a given section that would be most likely used in creating an abstract. In fulfillment of this goal, we needed to identify targets for each sentence input into our model. We identified these targets by first embedding article sentences using the SentenceTransformer package, which creates sentence embeddings of dimension 384. We similarly embedded article abstracts using the same method. We then iterated through each section's sentences and found the cosine similarity between the sentence with the article's abstract.

3. *Developing the LSTM models*

We further preprocessed our data in preparation for the LSTM models. In reading Qi et al.'s paper, we found that not only were sections within an article important, but also the order in which sentences come within a given section. As such, we appended to the beginning of our sentence embeddings their normalized sentence order, calculated by dividing the order in which the sentence came in a given section by the total number of sentences in that section. We then ensured that each section within our data had a uniform number of sentences by finding the section with the most number of sentences and padding the other sections with sentence "embeddings" of all 0s. Finally, we split each of our sections into training, validation, and testing sets using a 70-15-15 split.

For a given section's model, the inputs were the normalized order + embedded sentences. We decided to use LSTMs for this model given their ability to remember sequences and the sequential nature of sentences within an article. We specified a mask to ignore all 0.0 sentence embeddings, and we used 30 units in each of our models.

Finally, our models used a linear activation function, the adam optimizer, and evaluated loss based on the mean squared error of the prediction to the target.

We trained our four models over 25 epochs with a batch size of 64. We also implemented dynamic learning rate tuning to avoid exploding and vanishing gradients. If a given validation loss stayed consistent across 5 epochs, our model would decrease its learning rate until it reaches the minimum of 1e-6. Once the model was trained, we evaluated it against our test set. Here is a report of our test loss for each of our models.

Model	Initial Validation to Final Test Loss
Introduction	0.0331 → 0.0137
Methods	0.0297 → 0.0123
Results	0.0344 → 0.0131
Conclusions	0.0398 → 0.0101

Generating Extractive Summaries

Our summarizer takes as input a string of our article's text. It uses similar preprocessing techniques to the ones described above to extract the article's sections, embed its sentences, and concatenate the normalized order of its sentences. It then iterates through each section in the article and applies that section's model to the article text, resulting in a scoring of each of the sentences within the section. We then compiled summaries by going through each article's section and picking the top N sentences from that section, until we reached a maximum of 10 sentences. N was defined as follows: not every article had each of the four sections. Therefore, we determined how many of the four sections the article did have, M, and we calculed N by computing 10 // M + 1. We added 1 to give higher priority to the sentences in the first two sections, given Qi et al.'s finding that the Introduction in a particular article provided the most insight into its abstract.

To test this process, we pulled additional articles from Proquest TDM, focusing on climate journals that we did not use in our original data collection. We then removed those journals that didn't have the full article text and abstract, which resulted in approximately 230 articles to choose from. We then used a random generator to pick an article and its abstracts to develop summaries of.

Abstract	**Extracted Summary**
Abrupt monsoon onsets/retreats are indispensable targets for climate prediction and future projection, but the origins of their abruptness remain elusive. This study establishes the existence of three climatological Madden-Julian Oscillation (CMJO) episodes contributing to the rapid Australian summer monsoon retreat in mid-March, the South China Sea (or East Asian) summer monsoon onset in mid-May, and the Indian summer monsoon onset in early June. The CMJO displays a dynamically coherent convection-circulation structure resembling its transitionary counterpart, demonstrating its robustness as a convectively coupled circulation system and the tendency of the transient MJOs' phase-lock to the annual cycle. The CMJO is inactive during the boreal winter due to destructive year-to-year modulations of El Niño-Southern Oscillation. We hypothesize that the interaction between atmospheric internal variability (MJO) and the insolation-forced slow annual cycle generates the sudden monsoon withdrawal/onset during the boreal spring. Understanding the factors determining the timing and location of the MJO's phase-locking and its variability is vital for monsoon forecasting and climate projection.	Improving the understanding of the sudden changes and monsoon singularities in the annual cycle has profound implications for the seasonal forecasts and climate projections, as socio-economic activities, including agricultural planning and disaster mitigation, demand accurate monsoon onset and withdrawal predictions both presently and in the future. The summertime monsoonal CISO has been widely recognized to shape the monsoon onsets and retreats in East Asia, WNP, and South Asia (e.g., Ref. Daily atmospheric diabatic heating and sea surface temperature (SST) in the WNP might be important factors in maintaining the CISO related to the EA summer monsoon (EASM)16. Predicting monsoon onset, peak, and withdrawal has profound implications on socio-economic activity and natural disaster management51,52. A better understanding of the CISO and its relationship with the monsoon life cycle can advance our knowledge of the source of the S2S predictability and improve weather and climate predictions. Climate models' capability in simulating and predicting CISO and the abrupt monsoon transition remains ample room for improvement55–58. Through examining a 227-year daily precipitation record gathered in Seoul, South Korea, the characteristics of the rainy season, including the dates of onset, retreat, and summit, exhibit significant centennial variations, indicating the time- varying monsoon singularities detected by a 30-yr climatology change with time14. Future studies of the secular changes in CISO and monsoon singularity will help better understand the cause of climate change. Kajikawa, Y. and Yasunari, T. Interannual variability of the 10–25- and 30–60-day variation over the South China Sea during boreal summer. Dai, L., Cheng, T. F. and Lu, M. Anthropogenic warming disrupts intraseasonal monsoon stages and brings dry-get-wetter climate in future East Asia.

4. *Limitations*

Notably, our summaries do include a few unnecessary or incorrect sentences, which could be due to the sentence extraction method. In extracting sentences, we found that the NLTK package had trouble determining the sentences within citations, so that it would split citations into their most basic components. This is a limitation of our method. This limitation also relates to the difficulty of identifying section headers. We attempted to create an exhaustive list of headers and their mappings to the four sections, but the variability of header types was more complex than we originally expected. Ideally, we would have implemented a machine learning algorithm to identify sections.

Another limitation is in the development of the summaries. If we had more data to train on, we would have created a 5th model that was able to make our extractive summaries more coherent. We would have done so by generating a summary, embedding it, and comparing it to the cosine similarity of the article's abstract. This would have greatly increased the semantic and syntactic flow of our summaries. Additionally, we could have used this method to finetune the number of sentences to extract in the creation of the summaries, rather than just using 10 sentences as a default.

Methodology 2: Abstract to Title Summarization using HuggingFace

1. *Model-Building Process*

HuggingFace's extractive summarization process is designed to fine tune a more general NLP model for the specific task of summarization. To achieve this, a dataset of text and summary (created by HuggingFace) are passed in. We chose to use our own dataset of scientific journal articles to fine-tune this general model rather than the more traditional summarization dataset in order to create a model that was more well-suited for our specific task.

To prepare data to fit into the HuggingFace summarization training process, we needed to do some preprocessing, including appending the spring 'summarize:' onto the front of all abstract strings. Then text was tokenized and used to fine-tune the general NLP model. We used the Adam Weight Decay optimizer because it uses an adaptive learning rate and can prevent overfitting to our data. The fine-tuning was only run for one epoch, as it posed a significant time sink, but given more time, multiple epochs may have improved the results of our summarization model.

2. *Discussion*

Our fine-tuned model resulted in a unigram ROUGE score of 38.6996 and bigram ROUGE score of 18.6389, representing the overlap of n-grams produced by the abstractive summarization and the titles they were being trained against. These scores appear to be in line with a reasonably well-trained model. We were also able to reduce the loss from 2.6171 to 2.2893 through our fine-tuning.

While this process achieves better summarization of the dense, scientific language we needed the model to work on, it does have some drawbacks. We used the titles of the articles as the ground-truth summarizations for our model to check against. This meant that summarizations created by this trained model sounded more like titles describing topics of the article rather than informative summaries that are readable to the masses. Generally, this method was a good choice for the larger dataset of abstracts and titles which we were able to access, but the LSTM extractive summarization was a better choice for full article summarization.

Moral Foundations

Significance of Moral Foundations for Climate Communications

Discussions surrounding climate change encompass a broad spectrum of topics, including science, politics, society, ethics, morality, and individuals' perceptions of their role in the world. The way people understand and react to climate information is deeply influenced by their cultural background and personal experiences. These ingrained beliefs, attitudes, and values significantly determine how climate information is received and acted upon. Hence, tailoring climate communications to resonate with these deeply held values is essential for ensuring the message is effectively received by the intended audience.

Moral Foundations Theory offers a framework for understanding the varied lenses through which people view the world. Developed by psychologists Jonathan Haidt, Craig Joseph, and Jesse Graham, this theory posits the existence of five fundamental moral foundations: care/harm, fairness/reciprocity, ingroup/loyalty, authority/respect, and purity/sanctity. These five foundations, they argue, comprise the building blocks of morality, regardless of the culture. Moral foundations have been applied across disciplines, but have been particularly powerful in the study of political ideologies. It has also been used increasingly in Natural Language Processing as a way to classify the moral sentiments of different texts. Understanding these moral foundations can significantly enhance the effectiveness of climate communications by aligning messages with the moral values of the target audience, enhancing message engagement and impact.

Applications of Moral Foundations in NLP

In their 2021 paper, *Incorporating Moral Foundations Theory into Analyzing Stances on Controversial Topics,* Rezapour et al. explore how moral foundations influence online discourse regarding controversial topics (Rezapour et al.). Utilizing an expanded Moral Foundations Dictionary, the researchers analyzed a dataset of tweets categorized by stance on various social issues, including abortion, atheism, climate change, feminism, Donald Trump, and Hillary Clinton. The analysis revealed distinct "moral and lexical profiles" for different social issues, indicating that the expression of opinions on these topics is intertwined with the moral foundations of care, fairness, loyalty, authority, and purity. This paper informed our approach of using moral foundations as a way to categorize politically charged discussions in online discourse and also highlights the increasing relevance of NLP in the evaluation of moral foundations.

In the 2023 paper, *Automatic assignment of moral foundations to movies by word embedding*, González-Santos et al. explores the automatic assignment of moral foundations to movies using a word embedding-based approach, significantly outperforming existing methods in the scientific literature (González-Santos et al.).. They began with the Moral Foundations Dictionary (MFD), which categorizes words according to their moral foundation. This dictionary was then augmented using word embeddings to encompass a broader range of morally relevant terms. For each movie synopsis, pre-processed tags were analyzed, and semantic similarities to terms in the MFD were calculated using word embedding techniques. These similarities, ranging from 0 to 1, were only considered significant if they surpassed a 0.25 threshold, a standard set to minimize noise and align with precedents in the field. The analysis was performed using both Word2Vec and BERT models, comparing the original MFD with two expanded versions. The findings indicated that the smallest dictionary, when paired with Word2Vec, outperformed the larger dictionaries and BERT models in accurately assigning moral foundations to movie synopses. This research highlights the potential of moral foundation analysis in NLP, demonstrating its applicability beyond traditional text analysis to include diverse media content.

Methodology: Evaluating Moral Foundations of Subreddits Using Word2Vec and Cosine Similarity

We adapted the work of González-Santos et. al to design our approach to classifying reddit comments by their moral foundations.

1. *Moral Foundation Dictionary Generator*

We utilized the Moral Foundation Dictionary, crafted by the originators of Moral Foundations Theory, as our starting point. This dictionary categorizes words into 11 distinct groups: HarmVirtue, HarmVice, FairnessVirtue, FairnessVice, IngroupVirtue, IngroupVice, AuthorityVirtue, AuthorityVice, PurityVirtue, PurityVice, and MoralityGeneral. We excluded the MoralityGeneral category for its lack of alignment with a specific moral foundation.

To craft an expanded dictionary suited for analyzing online communications, we enhanced the original dictionary using fse/glove-twitter-200, pre-trained GloVe vectors derived from two billion tweets. For every word in the moral foundations dictionary, we identified the 100 most similar words above a specified similarity threshold. Through experimentation with similarity thresholds ranging from 0.7 to 0.9 and expanded dictionaries of approximately 300, 600, 900, and 2,000 words, we observed qualitative differences in the returned word types. Following the insights from González-Santos et al., which suggested that a smaller dictionary might yield better results, we decided on a 300-word Moral Foundation Dictionary, selecting the top 30 words for each foundation.

2. *Evaluating Moral Foundations of Reddit Comments*

After creating the expanded dictionary, we tokenized the comments from the Reddit dataset. We analyzed approximately 1.1 million comments across eight subreddits known for discussions on climate change: r/climate, r/science, r/climatechange, r/climateoffensive, r/environment, r/worldnews, r/climateskeptics, and r/politics. Given the tendency for online climate discourse to spike during major environmental events, we focused on the period immediately before, during (September 23, 2022 – September 30, 2022), and after Hurricane Ian. This timing was chosen to enhance the likelihood of capturing significant climate discussions and to investigate if such events alter the way people discuss climate online.

Our methodology mirrors the technique utilized by González-Santos et al., involving a pairwise comparison of the tokenized words in each comment with each word in the moral foundation dictionary. We compared these using the pre-trained word vectors from fse/glove-twitter-200, setting a threshold of 0.25 similarity for considering a word. Each comment was assigned 10 scores, ranging from 0 to 1, for each of the 10 moral foundations based on its similarity to the defining words of each foundation.

Moral Foundations Analysis

After classifying each of the 1.1 million comments, we assessed the data across subreddits and throughout the period surrounding Hurricane Ian. Our preliminary investigation revealed negligible differences between the counterpart moral foundations (e.g., comments scored similarly on HarmVirtue and HarmVice). For simplicity and clarity in our analysis, we consolidated the categories into five moral foundations: HarmVirtue and HarmVice into Care & Harm, PurityVirtue and PurityVice into Purity & Sanctity, and so forth. We then determined a Dominant Moral Foundation for each comment based on these aggregated values.

Across all examined timeframes and nearly all subreddits, Care & Harm emerged as the predominant moral foundation, with its presence ranging from 94.9% in subreddits like r/worldnews, r/politics, and r/climateskeptics to a minimum of 48.9% in r/science (See Figure 1).

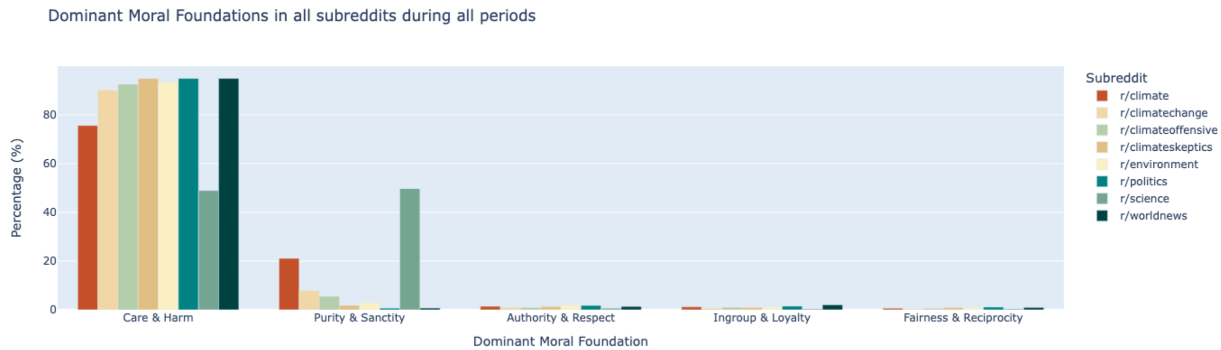


Figure 1: Dominant Moral Foundations in all subreddits during all periods

Notably, r/science stood out with Purity & Sanctity constituting 49.7% of comments, indicating a unique distribution of moral foundations within this community (See Figure 2). The subreddit r/climate also had a relatively high percentage of comments classified to this foundation at 21% (See Figure 3).

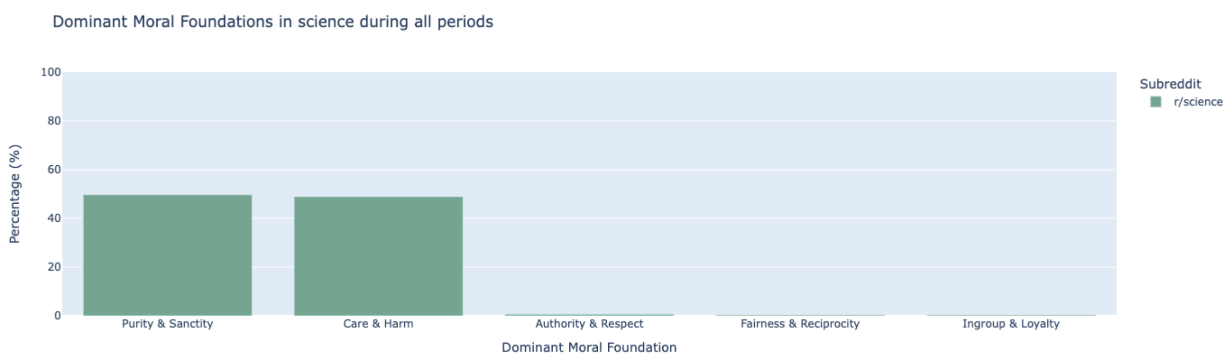


Figure 2: Dominant Moral Foundations in r/science during all periods

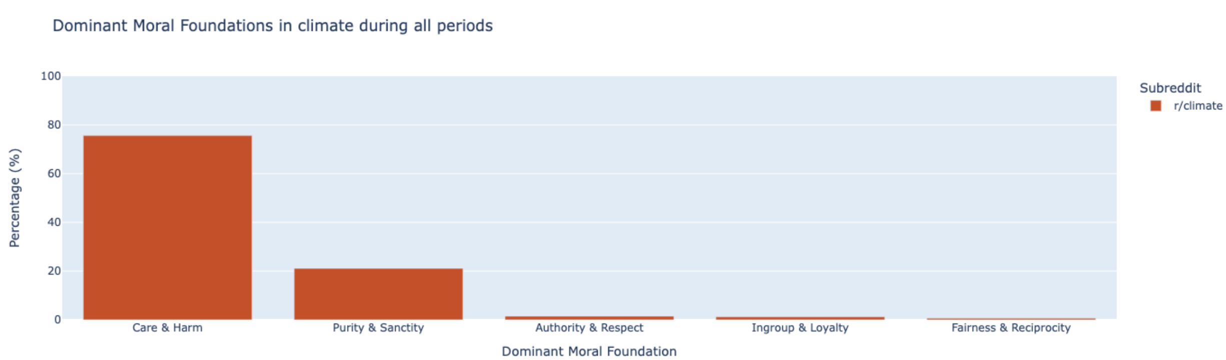


Figure 3: Dominant Moral Foundations in r/climate during all periods

Although other moral foundations did not prominently feature in any subreddit, it's important to note that this method primarily identifies the dominant moral foundation per comment. This does not imply the absence of other moral foundations in the discourse within these subreddits.

Based on these findings we observe the following:

1. **Discussions related to harm and care are prevalent across all analyzed climate-related subreddits:** Words under Care & Harm in the Moral Foundations Dictionary include words like: protect, shield, shelter, guard, preserve, suffer, kill, and endanger. Words similar to these appear frequently in comments of the subreddits we observed.
2. **The language of purity and sanctity was particularly notable in climate and science subreddits:** Words under Purity & Sanctity in the Moral Foundations Dictionary include words like: preserve, clean, pure, exploit, destroy, and disease. Words similar to these appear frequently in comments of the subreddits we observed.
3. **During Hurricane Ian, we observed a spike in the usage of Purity & Sanctity-related terms across nearly all subreddits, which later reverted to pre-disaster levels:** This suggests that natural disasters shift the moral valence with people people communicate online.

Figure 4 uses a WordCloud to show the most commonly used words across subreddits:

Figure 4: Most commonly used words across all subreddits and time periods

Based on previous literature using moral foundation analysis to draw distinctions between groups of differing political ideologies, we had hoped that the analysis of moral foundations over various subreddits would reveal some clear distinctions across groups (Rezapour, Dinh, & Diesner, et al., 2021; Graham, Haidt, & Nosek, 2009). We hypothesized that the users of r/climateskeptics would be more likely to use the moral foundations people who are politically conservative tend to rely on (i.e., authority/respect, ingroup/loyalty, and purity/sanctity) and the users of the other climate change subreddits would be more likely to use the moral foundations people who are politically liberal tend to rely on (i.e., fairness/reciprocity and care/harm). While the findings of our analysis were interesting and informative about the state of online discourse about climate, it did not provide the strong distinctions between groups that we had expected at the outset. Because of this, we transitioned to topic modeling as another way to identify distinct groups in climate discussions.

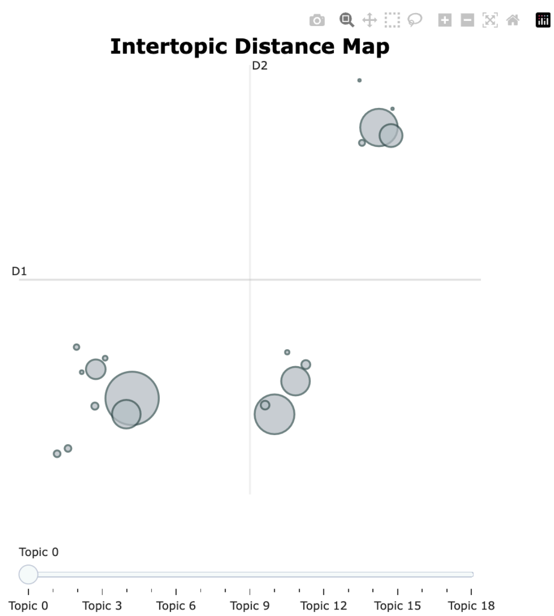
Topic Modeling:

To determine which topics pertaining to climate change might be most prevalent in climate change discussions on Reddit, we focused our topic modeling on the five subreddits specific to climate change and conducted topic modeling using Latent Dirichlet Allocation (LDA) and BERTopic. When implementing LDA, we first pre-processed the data using some of the tokenization we had already conducted prior to measuring moral foundations in language along with creating bigrams, lemmatizing the data, and calculating term frequency in the corpus of comments. We then trained a model on a subset of our Reddit comment data, but found the results underwhelming. To see if another model might perform better, we next implemented BERTopic. To implement BERTopic, we did not need to pre-process the data and provided data to this off the shelf model directly from our minimally cleaned Reddit data. BERTopic creates dense clusters by leveraging transformers and c-TF-IDF. We did not remove stop words from our final topics since BERTopic uses contextual information when making the topics (although we did experiment with how the topics turned out when we removed stop words, just out of curiosity). The embedding model we chose for the BERTopic implementation was this sentence embedding model from HuggingFace. We also experimented with different numbers of topics, ranging from the default number of topics BERTopic would produce for a text (this was usually well over 100 topics) to 50, 20, and 10.

The results from our various experiments with BERTopic were, similar to LDA, fairly underwhelming. We ultimately decided to produce 20 topics and then go through them manually to select ones that seemed sensical and pertinent to climate change. Those first five words in the first eight topics from this model are below.

Figure 5: The top eight topics in our final topic model.

From the above set of words we can see that some of the topics are more sensical and useful than others. The clusters from our final topic model can be seen in the below intertopic distance map.



The final set of ten topics we selected from our model of twenty topics is below. These lists of words are the representative words for each of these 10 topics.

Representation
['people', 'just', 'climate', 'like', 'dont', 'change', 'think', 'im', 'years', 'thats']
['climate', 'co2', 'change', 'water', 'just', 'energy', 'nuclear', 'temperature', 'like', 'years']
['people', 'bitcoin', 'just', 'oil', 'like', 'dont', 'crypto', 'money', 'capitalism', 'world']
['meat', 'vegan', 'animals', 'eat', 'animal', 'food', 'people', 'just', 'like', 'dont']
['solar', 'car', 'cars', 'evs', 'energy', 'panels', 'electric', 'people', 'power', 'need']
['court', 'law', 'constitution', 'states', 'abortion', 'supreme', 'federal', 'people', 'legal', 'state']
['heat', 'lapse', 'convection', 'adiabatic', 'air', 'rate', 'pump', 'ac', 'temperature', 'energy']
['pfas', 'lead', 'chemicals', 'sunscreen', 'soap', 'water', 'acid', 'ester', 'epa', 'teflon']
['women', 'men', 'gender', 'masculine', 'society', 'reveal', 'feminine', 'power', 'leadership', 'transgender']
['elon', 'elons', 'hes', 'innovator', 'better', 'sucking', 'ego', 'partisan', 'deserves', 'dick']

Bringing it all together: Creating the policymaker's toolkit

We created 1-pagers for policymakers to use to communicate accurate information about climate change to their constituents for each of the ten above topics. We created these 1-page toolkits for policymakers by pulling together the moral foundation analysis, short summary generation from journal articles, and long summary generation from journal articles. For each topic, we evaluated its top two moral foundations using our moral foundations classifier, calculated the similarity of an embedding of each topic to an embedding of the key words in our journal article repository, selected the most similar journal articles, then generated summaries of the journal articles most relevant to each of our topics. Finally, we compiled the moral foundations and journal article summaries together into a single document policymakers can use to communicate to their constituents about the climate change topics in which they're most interested.

Future Work

Extractive, Full Article Summarization

For the full article summarization, future researchers should focus on improving the identification of headers within article text and mapping them to the four sections. Additionally, the models themselves should be trained on a more robust dataset of climate articles to improve the ability to predict sentence importance. Finally, the construction of summaries should be iterated on more thoroughly, with methods implemented to make the extracted summaries more cohesive.

Network Analysis of Reddit Data

Future researchers could use the Reddit data to conduct a network analysis and examine conversations among Reddit users. This project treated the Reddit data as a corpus of data that we only subsetted by subreddit and time period. However, researchers could use user information connected to Reddit comments and submissions to develop a social network/graph. With this social network/graph, researchers could study how conversations progress on Reddit. In the context of this project, it could be interesting to pull the usernames of users in the r/climateskeptics group, look at their Reddit use in other subreddits, and analyze the text to see whether and in what context these users are persuaded about the existence of climate change.

Translating Scientific Language into Different Moral Foundations

Our stretch goal was to be able to take the extracted summaries of journal articles and the moral foundations measured from Reddit data and develop a translation of the summaries into the different moral frameworks (both those who believe in the existence of climate change and those who don't). The only evidence of similar work that we were able to find was a paper on Moral Style Transfer which attempted to perform a similar task as part of a class project. Though we were not able to complete this task we think that moral language translation would still have important and meaningful applications in climate communications. One major challenge will be retaining accuracy when performing moral transfer. It is important that any form of a moral translation model does not produce misinformation about important scientific topics.

Description of Work and Effort

Kate Habich

Kate took the lead on scientific article collection from ProQuest and the ProfileGenerator class, which pulled all of the pieces of the project together into a cohesive toolkit for policymakers, with contributions from all other members of the team at different points. She also wrote the entire abstractive summarization model, based on the HuggingFace documentation. In the process of scoping the project, she also took the lead finding literature to inform the extractive summarization model for scientific articles and lightly assisted on attempts to create the SAPGraph model based on the paper she found.

In writing the ProfileGenerator class, Kate was able to gain some familiarity with all aspects of the project, as each piece was called upon to create this final deliverable. These tasks also provided a great opportunity to brush up on class operations and usage of cosine similarity. She also learned the ins and outs of the HuggingFace summarization process, and understands it to a greater degree than homework assignments required. Finally, Kate gained a greater understanding of the many ways data scientists have used neural networks creatively to solve different types of NLP problems like scientific article summarization.

Kathryn Link-Oberstar

Kathryn supported with data collection of the scientific articles from ProQuest. She experimented with different approaches to building the expanded moral foundations dictionary and running moral foundation classification for all of the reddit data. She also developed a dashboard to communicate the findings of the moral foundations analysis.

She spent time reading papers related to current applications of NLP to perform moral foundation assignment, and used this work to use as a baseline for developing our own moral classifier specific to this task. She spent a significant amount of time reading research papers to better understand the state of tone translation in NLP, in hopes to reach the stretch goal of performing moral transfer. She tried to get up and running the models in the GitHub report for this report on moral transfer, though given the lack of documentation and missing files in the Github repository, was unable to implement this model for our task.

In addition to expanding her domain knowledge of applications of NLP in the social sciences, she also gained experience managing large datasets, learning to use Pythons' mutiprocessing package to parallelize the tokenization and moral sentiment classification process. She also learned how to use Dash and Plotly for data visualization through this project.

Chanteria Milner

Chanteria implemented a data cleaning class for the ProQuest articles. The articles were saved in an XML format, so this involved parsing the XML tree to pull relevant characteristics of the articles, including the text, abstract, authors, and keywords. Chanteria also created the class to word and sentence tokenize text using Spacy. Chanteria wrote the class that attempted to implement the SAPGraph summarization method, and finally developed the class that creates and implements the four LSTM models for full article text summarization.

Throughout this process, Chanteria knew how to do data cleaning and tokenization, but she learned more about the architecture of LSTMs, how to implement LSTM models, and how to measure cosine similarity with text embeddings. Finally, Chanteria thoroughly familiarized herself with the SAPGraph method code base and literature.

Jennifer Yeaton

Jennifer worked on development of our research questions using the Reddit data, reading about how we could use the Reddit data to study climate change and developing hypotheses about the use of moral foundations across subreddits and across time. Jennifer spent a significant amount of time reading journal articles about moral foundation measurement and about translating text into different moral foundations. Similar to Kathryn, Jennifer tried to implement the code of another research team that translated text into different moral foundations, but was not able to do so given the lack of docstrings in the code and the repository's lack of a readme with instructions for how to implement the code or how the data it was given needed to be pre-processed. Jennifer also spent time getting up and running on the Data Science Institute's cluster and used Chanteria's tokenization script on the cluster to tokenize the Reddit data. Jennifer implemented LDA and BERTopic. Jennifer worked with Kate to bring together the different pieces of the project into a single output.

Jennifer learned a lot through this project about working with Reddit data, the challenges of working with big data, and how to implement topic modeling. Implementing topic modeling was especially interesting to Jennifer because their background is in qualitative research in which they've had to manually code topics in interviews, and so it was really interesting to see how machine learning could help with this sort of work in the future.

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The code for this project is available at: https://github.com/ehabich/climate-conversations