You are right. I am ALARMED – But by Climate Change Counter Movement

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Abstract

The world is facing the challenge of climate crisis. Despite the consensus in scientific community about anthropogenic global warming, the web is flooded with articles spreading climate misinformation. These articles are carefully constructed by climate change counter movement (CCCM) organizations to influence the narrative around climate change. We revisit the literature on climate misinformation in social sciences and repackage it to introduce in the community of NLP. Despite considerable work in detection of fake news, there is no misinformation dataset available that is specific to the domain of climate change. We try to bridge this gap by scraping and releasing articles with known climate change misinformation.

1 Introduction

Climate change is one of the biggest challenges threatening the world, and we are at the defining moment. Rising sea levels, melting polar ice, changing weather patterns, severe droughts, and extinction of species are just some of the dreadful effects of this crisis. The Intergovernmental Panel on Climate Change (IPCC) in its 5th assessment report categorically concluded that humans are the main culprit and there is a need to limit global warming to less than 2°C.1 More recently, anthropogenic climate change has been at the heart of the Australian bushfires (van Oldenborgh et al., 2020), leading to the destruction of 17 million hectares of land and the death of a billion animals.2 During these times, we see articles with headlines such as Climate Change has caused more rain, helping fight Australian wildfires spreading misinformation to influence the narrative of climate change.3

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1https://www.ipcc.ch/report/ar5/wg1/
2https://www.aph.gov.au/About_Parliament/Parliamentary_Departments/Parliamentary_Library/pubs/rp/rp1920/Quick_Guides/AustralianBushfires
3https://www.heartland.org/news-opinion/newstoday/2020/02/climate-change-has-caused-more-rain-helping-fight-australian-wildfires

Table 1: Articles created by CCCM organizations.

The rise of this misleading information is part of a carefully crafted strategy by climate change counter movement (CCCM) organizations (Dunlap and Jacques, 2013; Boussalis and Coan, 2016; Farrell, 2016; McKie, 2018). These organizations use a formula consisting of a narrative structured around the principle ingredients of disinformation, misinformation, propaganda and hoax, sprinkled with the stylistic elements of sensationalism, melodrama, clickbait and satire, as can be seen in examples in Table 1. Their approach broadly mirrors that seen in fake news in the political arena (Rashkin et al., 2017), but is specifically tailored to the domain of climate change. This motivates the development of applications that can inform users via an automatic detection or alert system, similar to what we have seen for fake news (Rashkin et al., 2017; Pérez-Rosas et al., 2017; Jiang and Wilson, 2018).
the creation of misinformation datasets. The first public dataset for fake news detection (Vlachos and Riedel, 2014) and claim/stance verification (Ferreira and Vlachos, 2016) are moderately small with 221 and 300 instances, respectively. More recently, larger datasets have been developed, such as LIAR (Wang, 2017), collected from PolitiFact and labelled with 6 levels of veracity, and FEVER (Thorne et al., 2018), a dataset generated from Wikipedia with supported, refuted and not enough info labels. Extending the task to full articles, FakeNewsNet is a valuable resource (Shu et al., 2017, 2018). But to the best of our knowledge there is no misinformation dataset that is specific to the domain of climate change. We attempt to fill this gap by releasing a large set of documents with known climate change misinformation.

2 Related Work

The way the public perceives and reacts to the constant supply of information around climate change is a function of how the facts and narrative are presented to them (Flottum, 2014; Flottum et al., 2016). Flottum (2017) emphasizes that language and communication around climate change are significant, as climate is not just the physical science but has political, social and ethical aspects, and involves various stakeholders, interests and voices. A range of corpus linguistic methods have been used to study the topical and stylistic aspects of language around climate change. Tvinnereim and Flottum (2015) proposed the use of structured topic modelling (Roberts et al., 2014) to derive insights about the public opinion from 2115 open-ended survey responses. Salway et al. (2014) leveraged unsupervised grammar induction and pattern extraction methods to find common phrases in climate change communication. Atanasova and Koteyko (2017) analysed frequently-used metaphors manually in editorials and op-eds, and concluded that the communication in the Guardian (U.K.) was predominantly war based (e.g. threat of climate change), Seuddeutsche (Germany) based on illness (e.g. earth has fever), and the NYTimes (U.S.A) based on the idea of a journey (e.g. many small steps in the right direction).

In linguistics, style broadly refers to the properties of a sentence beyond its content or meaning (Pennebaker and King, 1999), and stylistic variation plays an important role in the identification of misinformation. Biyani et al. (2016) studied stylistic aspects of clickbait and formalised it into 8 different categories ranging from exaggeration to teasing, and proposed a clickbait classifier based on novel informality features. Similarly, Kumar et al. (2016) examined the unique linguistic characteristics of hoax documents in Wikipedia and built a classifier using a range of hand-engineered features. Rashkin et al. (2017) proposed using stylistic lexicons (e.g. Linguistic Inquiry and Word Count (LIWC)), subjective words, and intensifying lexicons for fact checking, and demonstrated that words used to exaggerate like superlatives, subjectives, and modal adverbs are prominent in fake news, whereas trusted sources are dominated by assertive words. Wang (2017) experimented with detecting fake news using meta data features with convolutional neural networks adapted for text (Kim, 2014).

Although articles with misinformation are predominantly human-written, the recent emergence of large pre-trained language models means they can now be automatically generated. Radford et al. (2019) introduced a large auto-regressive model (GPT2) with the ability to generate high-quality synthetic text. One limitation of GPT2 is its inability to perform controlled generation for a specific domain, and Keskar et al. (2019) proposed a model to tackle this. Building on this further, Dathathri et al. (2019) introduced a plug and play language model, where the language model is a pretrained model similar to GPT2 but with controllable components that can be fine-tuned through attribute classifiers.

3 Climate Change Counter Movement Organisations

Despite the findings of the IPCC’s 5th Assessment Report and more than 97 percent consensus in the scientific community to support anthropogenic global warming (Cook et al., 2013), coordinated efforts to tackle the climate crisis are lacking. This can be attributed to the rise in opposing voices including the fossil fuel lobby, conservative think-tanks, big corporations, and digital/print media questioning the science and research around climate change. These organisations are collectively referred to as climate change counter movement (“CCC”) organizations (Oreskes and Conway, 2010; Dunlap and Jacques, 2013; Farrell, 2016;
Argument | Frame
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CO2 is plant food and is good for the planet | Science
Climate change is natural and has always been changing | Science
We are entering another ice age | Science
Adapting to global warming is cheaper than preventing it | Policy
Renewable energy is way too expensive | Policy

Table 2: Examples of counter climate arguments and their frames.

Boussalis and Coan, 2016; McKie, 2018. McKie (2018) argues that the motivation behind these organizations is to maintain the status quo of the hegemony of fossil fuel-based neo-liberal global capitalism. These organizations are found around the globe and can masquerade as philanthropic organizations to fund climate misinformation (Farrell, 2019), hide behind libertarian ideas (McKie, 2018) to question the scientists, and augment scepticism to promote pseudo science or ‘alternative facts’. Some of these organizations have catchy names such as carbonsense.com or friendsofscience.org, and organize their own scientific conferences.

Oreskes and Conway (2010) concluded in their analysis that the strategies employed by CCCM to construct the narrative to spread misinformation resembles the ones historically used by the tobacco lobby. For instance, targeting researchers and questioning the methodology of their research, and blaming scientific standards are consistent strategies used by both CCCM and tobacco lobby groups (Oreskes and Conway, 2010; McKie, 2018). Dunlap and Brulle (2015); Farrell (2016); Boussalis and Coan (2016) categorized their misinformation arguments into 2 frames: science and policy. Science frame arguments question the scientific facts and deliberately plant a lie to sway the public towards pseudo science, whereas policy frame arguments target issues of cost and economy (e.g. carbon tax) or pass the blame for action to other nations. We present several examples of arguments in the science and policy frames in Table 2.

We believe the narrative of CCCM articles have two aspects: topical and stylistic. The topical aspects describe common issues discussed in CCCM articles (e.g. carbon tax, fossil fuel, and renewable energy). The stylistic aspects capture how the narrative is presented — e.g. the use of exaggeration and sensationalism, as evident in the examples in Table 1 — and bear similar characteristics to fake news.

4 Dataset

To construct our dataset, we scrape articles with known climate change misinformation from 15 different CCCM organizations. These organizations are selected from three sources: (1) McKie (2018), (2) desmogblog.com, a website that maintains a database of individuals and organizations that have been identified to perpetuate climate disinformation; and (3) an organizations cited on the website selected from above 2 sources. A number of considerations were made when developing the dataset:

- We only scrape articles from organizations active in English-speaking countries: the United States, Canada, United Kingdom, Australia, and New Zealand.
- A considerable number of organizations are either dormant or have a very low level of activity. To make sure our dataset is up to date, we only scrape articles from organizations with a reasonable level of activity, e.g. they publish at least 1 article every month, and their latest publication is in 2020.
- We set a minimum and maximum threshold of 10 and 400 articles respectively for each organization. We set a maximum threshold so as to avoid bias towards one organization. Note, however, that there is a considerable variance in the article length for different organizations. For instance, one organization with only 10 articles has an average length of 342.1 words, while another organization with 400 articles has an average length of 85.8 words.
- As explained in Section 3, counter climate arguments can be broadly categorised into the science and policy frames. As organizations generally prefer one type of frame in their narrative, we manually identify frames associated with organizations, and select a set of organizations that produces a balanced representation of both frames in the dataset.

We split the documents into training and test partitions at the organization level, where the training set comprises 12 organizations and the test set

https://www.desmogblog.com/global-warming-denier-database
3 organizations. We split at the organization level because it allows us to test whether detection models are able to generalize their predictions to articles published by unseen/new CCCM organisations. We present some statistics for the training documents in Table 3, and the list of organizations is provided in the supplementary file.

4.1 Test data
We extend our test set to include documents that do not have climate change misinformation, to create a standard evaluation dataset for climate change misinformation detection. We collect documents from reputable sources, some of which are not climate-related, and some are satirical in nature. Sources of the full test documents are as follows:

- **Guardian**: A trusted source for independent journalism. We scrape articles under the category of climate change from both its U.K. and Australian editions. These articles test whether a detection system can correctly identify these articles as not having climate change misinformation.

- **BBC**: Similar to Guardian, we scrape articles from their website under the category of climate change.

- **Newsroom**: This is a dataset released by Grusky et al. (2018) and consists of articles and summaries compiled from 38 different publications. We take a random sample of articles which are not climate-related. These articles test whether a detection system is able to identify non-climate-related articles as not having climate change misinformation.

- **Beetota Advocate**: This is an Australian satirical website which publishes articles on current affairs happening locally and internationally; we scrape articles related to climate change. Although there is a tone of sensationalism in the writing, the articles are created with the intent of humour. An example of a Beetota Advocate article is given in Table 4. These articles test whether detection models are able to distinguish them from CCCM articles, as both have similar stylistic characteristics.

- **Sceptical Science Arguments (SSA) and Sceptical Science Blogs (SSB)**: This resource focuses on explaining what science says about climate change. It publishes general climate blogs and counters common climate myths by putting forth arguments backed by peer-reviewed research.

- **CCCM**: These are articles from the 3 CCCM organizations, as detailed in Section 4. These documents are the only documents with climate change misinformation in the test data.

Table 4: A Beetota Advocate article on climate change.

PM Meets With Cricket Side To Discuss The 1.7m Hectares Of NSW Forests Destroyed By Bushfires. Not even six months after being officially elected as the Australian Prime Minister with absolutely no policies, let alone any acknowledgement of his government’s denialism-led inaction on climate change, Scott Morrison has today had the opportunity to meet some more sportsmen! While the drought-stricken communities of rural Australian continue to burn at the hands of record-breaking and out-of-control bushfires, ScoMo has today met with the Australian cricket side for his ideal media appearance. The cricketers appeared distressed while also having to pose for goofy photos with the Prime Minister. planet’s temperature that will result in the certain deaths of the billions of people that haven’t been given permission to join Gina Rinehart and her Liberal Party employees in the spaceship.

Table 5 contains statistics of the test set.

5 Conclusion
We introduced climate misinformation to the domain of fake news and in the community of NLP.

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### Table 3: Statistics of CCCM training data

| # Organizations | 12  |
|-----------------|-----|
| # Articles      | 1168|
| Mean Length     | 559.3|
| Median Length   | 332.0|
| Std Length      | 640.2|

Table 3: Statistics of CCCM training data

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5 https://summari.es/
6 https://www.betootaadvocate.com/
7 https://www.skepticalscience.com/
We explored the literature around emergence of CCCM organizations, the strategies and linguistic elements used by these organizations to construct a narrative of climate misinformation. To help in countering its spread, we scrape articles with known sources of misinformation and release it to the community.

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| Organization Name                          | Website                                      |
|-------------------------------------------|----------------------------------------------|
| Australian Environmental Foundation       | https://www.australianenvironment.org/      |
| Australian Climate Madness                | https://australianclimatemadness.com/        |
| The Carbon Sense Coalition                 | https://carbon-sense.com/                    |
| CO2 Coalition                             | https://co2coalition.org/                    |
| Fraser Institute                          | https://www.fraserinstitute.org/             |
| Friends of Science                        | https://friendsofscience.org/                |
| The Global Warming Policy Foundation      | https://www.thegwpf.org/                     |
| Heartland Institute                       | https://www.heartland.org/                   |
| The Institute of Public Affairs           | https://ipa.org.au/                          |
| Manhattan Institute                       | www.manhattan-institute.org/                 |
| New Zealand Climate Science Coalition     | https://www.climatescience.org.nz/           |
| Watts up with that                        | https://wattsupwiththat.com/                 |
| Cato Institute                            | https://www.cato.org/                        |
| The BFD                                   | https://thebfd.co.nz/                        |
| Heritage Foundation                       | https://www.heritage.org/                    |

Table 1: Table of CCCM Organisations