## NYTAC-CC: A Climate Change Subcorpus based on New York Times Articles

### Anonymous ACL-IJCNLP submission

### Abstract

Over the past decade, the analysis of dis-013 courses on climate change (CC) has gained 014 increased interest within both the social sci-015 ences and the NLP community. Textual re-016 sources are crucial for understanding how narratives about this phenomenon are crafted and 017 delivered. However, while there is growing at-018 tention on social media resources, there still 019 is a scarcity of datasets that cover CC in 020 news media in a representative way. This pa-021 per presents a CC-specific subcorpus extracted 022 from the 1.8 million New York Times Annotated Corpus, marking the first CC analysis on 023 this data. The subcorpus was created by com-024 bining different methods for text selection to 025 ensure representativeness and reliability of the 026 subcorpus, which is validated using Climate-027 BERT. To provide initial insights into the CC 028 subcorpus, we discuss the results of a topic modeling experiment (LDA). These show the 029 diversity of contexts in which CC is discussed 030 in news media over time, which is relevant for 031 various downstream tasks. 032

## 1 Introduction

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We present NYTAC-CC, a climate change (CC) topic-specific subcorpus of news media articles covering a 20-year period, based on the *New York Times Annotated Corpus* (NYTAC). NYTAC is a collection of 1.8 million articles published by the paper between 1987 and 2007 and made available by the *Linguistic Data Consortium*<sup>1</sup>. The original corpus, and thus also the subcorpus, includes a variety of metadata, including the 'desk' (the newspaper branch) and both manually- and automatically-labeled tags that categorize the content. Furthermore, a sizable subset of the articles includes handwritten summaries.

NYTAC has been used for various research purposes in the Natural Language Processing (NLP)

<sup>1</sup>http://ldc.upenn.edu

community since its release in 2008, which allows the CC research community to profit from 15 years of related NLP work (e.g. Zhang et al. (2015); Alonso et al. (2010)). In addition, given the extensive temporal coverage, the NYTAC-CC subcorpus serves as a valuable resource for investigating how CC has been discussed and portrayed in the news media over time, including how early CC debates were embedded within other subtopics such as domestic and foreign policy, science reporting, or articles from the domains of arts and culture. Compared to other CC-related resources that focus on shorter documents, the NYTAC-CC subcorpus includes documents of variable length. 050

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The contribution of this paper is threefold:

- *First*, we present the NYTAC-CC subcorpus (by publishing the filenames) and its construction using blending of dictionary-based and supervised methods in order to ensure representativeness as well as validity and reliability, which are key in social science research (cf. Kantner and Overbeck (2020)). This hybrid approach is designed to address the challenges associated with refining a topic-specific subcorpus or extracting relevant information from a larger, existing corpus. It aims to overcome the limitations of traditional sampling techniques, which often involve retrieving articles via a small set of keywords or bigrams and can lead to the inclusion of false positives in the datasets.
- *Second*, to demonstrate the representativeness of the subcorpus and its reliability for further downstream tasks, we illustrate the results of a classification experiment using ClimateBERT (Webersinke et al., 2022), a BERT-based model specifically trained on CCrelated texts, to validate that the articles in our NYTAC-CC subcorpus are true positives.

100 • Third, to gain initial insights into the coverage 101 of the CC subcorpus, we use keyword analysis and topic modeling (specifically LDA) 102 to track specifics of climate change reporting 103 over the 1987-2007 time span. Our results 104 show important trends over time, including 105 key periods of reporting and a large variety of 106 issue contexts in which CC is discussed. 107

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Thus, our goal is to utilize the NYTAC corpus to gain a comprehensive picture of the NYT's coverage of CC during the specified time period through our subcorpus. While several studies have examined U.S. print media's reporting on anthropogenic CC (see Section 2), to our knowledge, this is the first work that specifically addresses the 20-year period covered by the NYTAC.

The rest of the paper is structured as follows: Section 2 summarizes relevant related work. Section 3 describes the process of creating the topicspecific subcorpus from the NYTAC through the aforementioned combined method, as well as results from classification task using ClimateBERT to validate the NYTAC-CC subcorpus. Section 4 offers key observations on the content and distribution of NYTAC-CC articles, including the outcome of an LDA experiment for unsupervised sub-topic exploration within the subcorpus. We conclude in Section 5 with suggestions for future work based on the subcorpus.

### **Related Work: Climate Change in** 2 News

Despite the growing interest in addressing climate change among various academic communities, as pointed out by Luo et al. (2020), the topic has so far received limited attention within the 'core' NLP community. This is largely due to the NLP field's focus on standardized datasets and shared tasks, 137 where the topic of CC has been scarcely addressed. Efforts can be observed within the context of social media, with datasets made available for CC-related 140 tasks (Effrosynidis et al., 2022; Samantray and Pin, 2019). Other existing datasets mostly remain limited to the sentence or paragraph levels (Leippold and Varini, 2020; Diggelmann et al., 2020; Laud et al., 2023). However, there remains a scarcity of NLP works (focusing here on English text) that address the CC discourse at the news article level, where the majority of studies on CC within traditional media have been conducted in various social science disciplines (Diehl et al., 2019; Shehata

et al., 2021). This section will focus on prominent work targeting traditional news media.

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A widely-cited early study by Trumbo (1996) examined the framing techniques used by various "claim makers" in the online editions of five U.S. newspapers. After querying with different terms and manually filtering the results, the remaining articles were thoroughly investigated. Boykoff (2008) later studied the "claims and frames" issue in a similar manner.

Legagneux et al. (2018) conducted a comparative study of scientific literature and press articles to investigate coverage differences between CC and biodiversity. They analyzed materials from the USA, Canada, and the United Kingdom spanning 1991 to 2016, using representative keywords to query and retrieve relevant content. Boykoff and Boykoff (2007) analyzed CC coverage in U.S. TV and newspapers (1988-2004) to see if journalistic norms like personalization, drama, and balance hindered reporting on anthropogenic CC. Their study, using manual coding, revealed that an emphasis on balance and drama often gave undue prominence to fringe scientists. Other studies examined the frequency of CC mentions, or the 'attention cycle'. Brossard et al. (2004) compared CC reporting between the NYT and the French Le Monde. Grundmann and Krishnamurthy (2010) analyzed newspapers from four countries, enhancing article counts with word frequency and collocation analyses using corpus-linguistic tools, with outcomes manually interpreted. The work of Stecula and Merkley (2019) highlights one of the few instances where NLP technology is extensively used to analyze CC in newspapers. They applied supervised classification to construct a corpus and identify frame categories within four U.S. papers. Continuing within the NLP field, Webersinke et al. (2022) use a corpus that includes, among its subsets, the NEWS dataset containing CC-related news articles. However, the dataset is not publicly available, nor are the specifics on how these data were retrieved detailed. Mishra and Mittal (2021) curated a dataset of 11k news articles by web scraping from the Science Daily website.

In conclusion, there remains a scarcity of corpora containing larger text units like entire articles, essential for the NLP community investigating climate change (CC) narratives in traditional media or performing various downstream tasks involving news articles.

### **3** Building the NYTAC-CC Subcorpus

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### 3.1 Challenges in CC Text Selection

In the LDC release, the New York Times Annotated 203 Corpus comprises 1,855,658 articles published be-204 tween 1987 and 2007, each provided as a single 205 XML file. The corpus contains detailed metadata, 206 including information about the date, author, and 207 newsroom desk that published the article. Addition-208 ally, the documents are manually annotated with 209 information about locations, people, organizations, 210 and topics that are prominent in an article. Anno-211 tators could choose as many tags as they wished 212 from a set of entities that appears to have expanded 213 over the years. The topic labels are generally not 214 sufficient for our purpose, that is, finding all CC-215 related articles, because (i) not all articles are la-216 beled; (ii) some labels of potentially CC-relevant 217 text are overly broad, e.g., 'weather,' which also 218 encompasses many non-CC topics; and (iii) some 219 articles we consider CC-relevant are tagged with 220 labels that do not relate to climate change.

Our goal is to design a retrieval method that not only meets the requirements of validity and reliability but also emphasizes representativeness, ensuring the corpus adequately covers the range of content related to the specific subject matter it aims to represent. Traditional approaches, such as the use of keywords or n-grams, can be inadequate if used alone and can lead to misclassifications due to both false positives and false negatives. This holds even with advanced models, particularly when tasked with processing large linguistic units such as entire articles (Leippold and Varini, 2020). The changing use of language in time-spanning corpora can further challenge single-method approaches since they must handle texts that, although consistent in topic, may cover the phenomenon in varied ways over time.

> Moreover, we aim for an approach that is reproducible, i.e., that can also be applied to other corpora that do not come with this type of metadata. We have therefore opted for a hybrid approach that combines the advantages of both keyword-based methods and automatic classification, while also aiming to overcome the weaknesses of both.

### 3.2 Our Hybrid Approach

To refine our method, we first reviewed the methods for text retrieval that have been used in previous studies on (CC) discourse, such as those mentioned in Section 2, as well as in other work targeting blogs and Twitter. We identified the following approaches:

- Search with bigrams: typically, this involves terms like "climate change," sometimes accompanied by one or two others, notably "global warming" and "greenhouse effect"; e.g., (Trumbo, 1996; Legagneux et al., 2018)
- Search with a longer list of keywords, followed by manual filtering; e.g., (Hulme et al., 2018; Leippold and Varini, 2020)
- 3. Complex Boolean queries with keywords and operators such as AND, OR, NOT; e.g., (Schmidt et al., 2013)
- 4. Manual annotation of training data followed by supervised classification; e.g., (Stecula and Merkley, 2019)

As a first exploratory step, we experimented with method (1), obtaining the expected unsatisfactory results. We subsequently refined our retrieval process from the NYTAC by extending methods (2) and (4).

Texts that we consider relevant for the CC topic should deal with some aspect of anthropogenic climate change, relate information about it, or convey a stance on the existence or urgency of the problem. It is not sufficient to merely mention CC in passing, for example, as one among a series of other ongoing crises. The most challenging judgments arise with texts that deal with an environmental problem possibly related to climate change (such as CO<sub>2</sub> emissions, ozone depletion, deforestation, etc.), even though CC is not explicitly mentioned. Our criterion is that the connection to CC must be clearly inferable from the text. For instance, an article that provides merely statistics on different types of air pollution would not qualify as CC-related unless the link to climate change is made explicit by the author.

**Bigram search.** Initially, we experimented with a list of bigrams<sup>2</sup> sourced from the BBC Climate Change Glossary<sup>3</sup>. This was done to cover terminologies that were used over the two decades

<sup>3</sup>https://www.bbc.com/news/ science-environment-11833685

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<sup>&</sup>lt;sup>2</sup>climate change, global warming, greenhouse effect, acid rain, ozone layer, greenhouse gases, fossil fuels, greenhouse emissions, ice shelves, ice sheets, rising sea, sea levels, Kyoto Protocol, Montreal Protocol, carbon footprint, carbon dioxide, carbon neutral, emission trading, feedback loop, global dimming, renewable energy, Stern Review

spanned by the corpus. We applied the criterion 300 301 that an article must contain at least one instance of one of the bigrams, which led to the retrieval of 302 10,707 articles. Upon manual inspection, we found 303 that many articles were false positives, addressing 304 general environmental problems but not specifi-305 cally related to climate change. Conversely, many 306 articles we regarded as relevant did not contain the 307 bigram "climate change" (searching for this bigram 308 yielded only 2,080 texts). Consequently, this led us 309 to seek a more elaborate approach. 310

311 Keyword search. In response to the limited per-312 formance of the bigram search, we proceeded to ex-313 tract CC-related articles using keywords employed 314 by Hulme et al. (2018) for identifying all topic-315 relevant articles in the journals *Nature* and *Science* 316 between 1966 and 2016.<sup>4</sup> To these, we added 317 the keyword "Kyoto." An article had to contain 318 at least two different keyword types to be selected. However, the resulting subcorpus still contained 319 many false positives. One source of these was very 320 long list-like articles from the corpus, categorized 321 as "Listing," "News Summary," "Business Digest," 322 "Inside," or "Observatory," which combined a vari-323 ety of different news in a single document. In the 324 interest of homogeneity, we removed all articles 325 from these categories, which led to an intermediate 326 corpus consisting of 12,883 articles. 327

328 Text ranking and supervised classification. То 329 overcome the presence of false positives within the 330 intermediate corpus, we decided to implement an 331 additional, more elaborate filtering step on the in-332 termediate corpus. Initially, we ranked the articles 333 for topic relevance, using a score based on accu-334 mulated keyword weights. This score reflects both 335 the frequency of the keywords and their position 336 within the article, as content in the beginning is gen-337 erally considered most important. For instance, we 338 multiply the number of keyword occurrences per sentence by a score representing sentence promi-339 nence (1 for the first sentence, 0.9 for the second, 340 0.8 for the third, and so on). For example, if the 341 word "climate" appears once in the second sen-342 tence, 0.9 \* 1 is added to the overall score of the 343 text. 344

> After automatically ranking the articles, we selected 450 articles for manual tagging: the top 150, the last 150, and 150 from the middle. We manually

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assessed them to determine if they were at least partially about climate change. An article received the label '1' if it referenced the problem of global climate change or an aspect thereof—consistent with our previous characterization. It was labeled '0' if it did not meet this criterion. Similarly, articles where the words 'climate' and 'weather' were used figuratively, as in 'They weathered the climate,' were also labeled '0'. 350 351

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We used the manually-annotated data to train and test an XGBoost classifier, which we configured to differentiate between CC-related and non-CC articles. The features used included keyword counts (those from (Hulme, 2009), plus 'Kyoto'), the 50 most frequent 'topic' labels from the article metadata, and several binary features: whether an article was published by (i) the 'Dining' or 'Style' desks or by (ii) other desks; whether it was published on the weekend; whether a keyword appeared in the title or the first paragraph; and whether the article was (i) an opinion piece or a letter versus (ii) another type of article.

The classifier achieves a precision score of 1.0 and a recall score of 0.94 on our held-out evaluation set of 100 texts. Subsequently, we used the classifier to label the entire intermediate corpus. A total of 9,067 articles were labeled as -climate (not CCrelated), while 3,630 were designated as +climate (CC-related), forming what we now refer to as our final 'NYTAC climate change subcorpus.'<sup>5</sup> The graph in Figure 1 illustrates the features that had the greatest impact on the classification decisions.

# 3.3 Evaluating the Subcorpus with ClimateBERT

We aim to demonstrate (i) the relevance of our 3,630-article-subcorpus in genuinely consisting of climate change (CC)-related articles and, thereby, (ii) the validity of our combined method in retrieving topic-consistent texts from a larger and heterogeneous collection while minimizing the inclusion of false positives. To perform that validation, we conducted experiments with Climate-BERT, specifically  $ClimateBert_F$  (Webersinke et al., 2022), a BERT-based model trained on CC-related texts. In particular, we used *distilroberta-base-climate-detector* from the Hugging Face platform<sup>6</sup> (Bingler et al., 2023), a fine-tuned version of  $ClimateBert_F$  with a classification head for

<sup>&</sup>lt;sup>4</sup>climate, atmosphere, weather, warming, carbon, greenhouse, pollution

<sup>&</sup>lt;sup>5</sup>To facilitate future research, we will make the IDs of the texts available upon the publication of this paper. <sup>6</sup>https://huggingface.co/

400 detecting climate-related paragraphs. Given its spe-401 cialization in CC-related texts, we deemed Climate-BERT a very suitable tool to confirm the accuracy 402 of our dataset. In doing so, we are also indirectly 403 assessing the model's capability in detecting CC-404 related content within larger portions of texts. As 405 the model's context length is limited to 512 tokens, 406 we addressed this limitation by adopting two differ-407 ent approaches, which we describe below. For our 408 experiments, we used only the text of the articles 409 as input data, without employing any advanced pre-410 processing steps or including additional metadata. 411

In the first approach, longer texts were truncated 412 due to the model's limited context length. Of the 413 3,630 instances, the model recognized 3,468 arti-414 cles as +climate. We conducted a manual inspec-415 tion of the remaining 162 texts that the model clas-416 sified as -climate, i.e. as false positives for our 417 corpus. We found that the model clearly misclassi-418 fied 75 texts, which after manual inspection turned 419 out to include relevant sections on CC. However, 420 in part, this was due to the model's input limita-421 tions, which led to the misclassification of longer 422 texts containing relevant climate-related parts later 423 in the text. More qualitative insights on these 162 424 texts initially identified by ClimateBERT as false 425 positives are provided in Section 4.1. In addition, 426 we attempted a second approach to overcome the context length constraint by using a sliding win-427 428 dow technique. This involved creating chunks of longer texts (> 512 tokens), classifying each chunk, 429 and labeling the entire text as +climate if any of the 430 chunks were labeled as such. This second approach 431 led to significantly different results, as only 3 out 432 of 3,630 instances were labeled -climate. These 433 results demonstrate both the representativeness of 434 our corpus and the validity of our hybrid subcorpus 435 selection method. In addition, we show how auto-436 matic classification models can be limiting when 437 dealing with long text units, therefore reinforcing 438 the need for a combined approach to build topic-439 relevant (sub)corpora. 440

### 4 Overview of the NYTAC-CC Corpus

In this section, we aim to provide an initial
overview of the coverage within the NYTACCC, including specifics on the distribution of articles over time and an initial examination of the
subtopics it portrays. We begin by illustrating a
qualitative content analysis of the articles classified as false positives by ClimateBERT. Following

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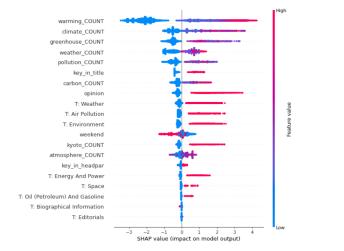


Figure 1: High-impact features in classifying "climate change" articles

this, we conduct a straightforward yet informative keyword-based analysis and a topic modeling experiment that offers a preliminary insight into some of the key subtopics covered by the subcorpus.

## 4.1 Qualitative Analysis of Misclassified Articles

As discussed in Section 3.3, we performed a manual inspection of the 162 articles that ClimateBERT initially classified as false positive within our subcorpus. We found that 75 out of these 162 articles were, in fact, clearly related to CC. Specifically, 48 of these articles included substantial discussions on CC and related issues occurring after token 512, which indicates that the model's limited context length significantly impacted its classification accuracy. Furthermore, 27 articles were either entirely about CC or contained several paragraphs explicitly detailing CC stories before token 512. These discussions often intersected with other themes such as politics (e.g., conferences on CC) and population effects (e.g., impacts of CC on specific regions).

Despite not being the main focus, the remaining articles still mentioned CC-related information. Specifically, in 51 articles, CC was mentioned within sections that were marginally related to the main narrative, showing that CC could be interwoven with discussions on other topics. Additionally, in 36 articles, CC played a secondary role, being mentioned as part of a longer list of issues or events or merely in passing—for instance, some articles mentioned the Kyoto Protocol as an example, while others used global warming metaphorically.

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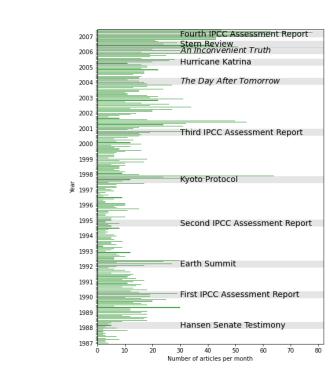


Figure 2: Monthly article count in CC subcorpus

#### **Temporal and Keyword highlights** 4.2

We examine the temporal distribution of articles and the usage of key lexical features in our corpus. This analysis helps illuminate trends and shifts in the coverage of climate change over time. When looking at the distributions of articles over time (Figure 2), we observe a peak around the year 1990, with up to 50 articles on climate change per month. This is followed by a drop in coverage, with only 20 articles per month during the mid-90s. From the beginning of 1998 – and following the adoption of the Kyoto Protocol in December 1997 – the curve shows a steady rise with intermittent bursts in coverage. In the figure, we have inserted several important 'climate events' (taken from various online sources) corresponding to the years they occurred.

The frequency ratios of the top eight lexical fea-542 tures determined by the classifier (cf. Figure 1) 543 over time in Figure 3 illustrate the dominance of 544 'greenhouse' in the late 1980s. 'Warming' remains 545 the most frequent term throughout, but in the fi-546 nal years, 'climate' gains prominence, suggesting a shift of term preference from 'global warming' to 'climate change'-a transition noted in various 548 other studies as well. Also, the two 'Kyoto' events 549

are clearly visible: the international accord was reached in 1997, and the Bush administration's decision not to ratify it occurred in 2001.

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Upon examining the co-occurrence of the top keywords, we noticed that 'atmosphere', 'weather', 'pollution', and 'Kyoto' are outliers, generally cooccurring less frequently with other terms. This observation supports our earlier description of varying degrees of CC-topicality: many articles discussing weather or pollution primarily address these issues directly, mentioning climate change only tangentially, which results in a low frequency of other prominent CC terms in these articles.

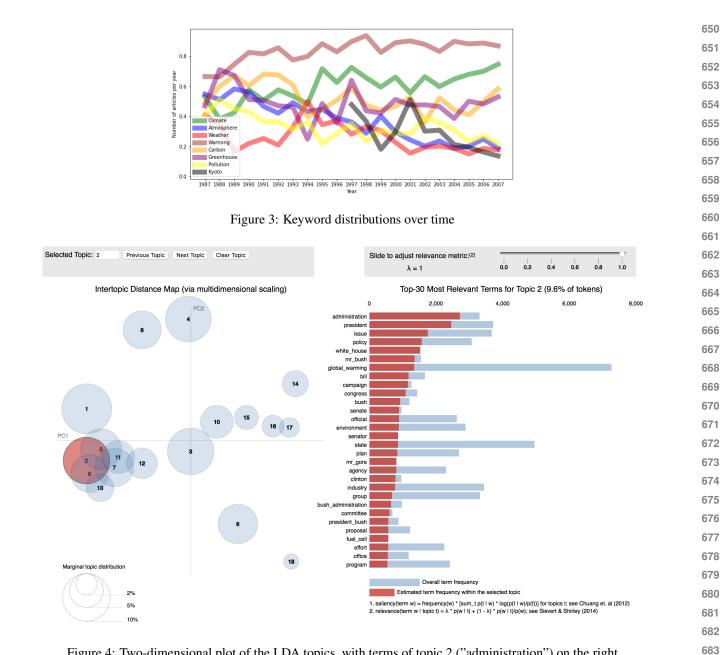
### Structuring the Document Set with LDA 4.3

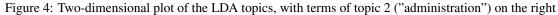
Building on the basic statistics previously discussed, we delved deeper into the range of subtopics within the CC corpus using topic modeling, specifically Latent Dirichlet Allocation (LDA). This approach helps to uncover underlying thematic structures in the data, which are not immediately apparent from simple keyword analysis.

**Preprocessing Steps** To prepare the texts for LDA, we implemented several preprocessing steps on both the titles and bodies of the articles. These included: removing punctuation symbols; lemmatizing words to reduce them to their base or dictionary form; applying POS-tagging to identify parts of speech, as we focused on nouns; lower-casing all words to ensure uniformity; joining commonly co-occurring bigrams into single terms to preserve significant phrases. Additionally, to refine the focus of our topic modeling, we retained only words that met all the following criteria: (i) Classified as nouns or proper nouns, (ii) Ranked among the top 10,000 nouns and proper nouns by frequency, (iii) Comprised of more than two letters. We restricted our analysis to nominal phrases, concentrating on entities and their relationships within the topic model to emphasize concepts central to the content of the articles. This simplification helps to avoid the dilution of thematic significance by less informative parts of speech and is supported by transforming common bigrams into single pseudowords for clarity and consistency.

Model Selection The best LDA model was chosen based on the coherence score, calculated using the Python *Gensim* library<sup>7</sup>. This method ensures that our model selection is objective, minimizing

<sup>&</sup>lt;sup>7</sup>https://pypi.org/project/gensim/





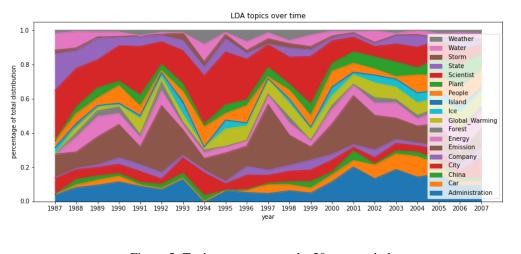


Figure 5: Topic coverage over the 20-year period

700 subjective interpretation in the analysis. We pri-701 oritized coherence to enhance the likelihood that 702 the topics generated by the model are interpretable and meaningful. The optimal model identified con-703 sists of 18 topics, with a coherence score of .56, 704 indicating a reasonable level of interpretability. For 705 each topic, we chose the highest-ranked term as the 706 'name' of the topic and list five additional represen-707 tative terms as follows: 708

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- 1. **emission:** country, world, greenhouse\_gas, carbon\_dioxide, global\_warming
- 2. **administration:** president, policy, white\_house, bill, congress
- 3. **people:** time, life, book, world, earth
- 4. **scientist:** temperature, climate, study, research, university
- 5. energy: oil, fuel, gas, production, power
- 6. **city:** new\_york, people, park, town, mayor, manhattan
- 7. **company:** business, project, program, group, director
- 8. **global\_warming:** report, climate\_change, scientist, panel, editor
- 9. **plant:** coal, company, emission, power, utility
- 10. water: area, land, river, population, fish
- 11. state: pollution, air, ozone, epa, smog
  - 12. **china:** government, people, war, security, country
- 13. car: vehicle, fuel, gasoline, hydrogen, auto
  - 14. ice: sea, arctic, ocean, glacier, bear
    - 15. forest: tree, plant, species, fire, crop
      - 16. **weather:** winter, temperature, snow, degree, heat
    - 17. **storm:** el\_nino, drought, hurricane, wind, flood
  - 18. **island:** bird, beach, garden, long\_island, sand

741 As is common with topic models, some overlap 742 between topics can occasionally be observed when 743 examining the complete top-30 term lists, for ex-744 ample, between topics company and plant. Addi-745 tionally, we find some apparent 'outlier' terms in 746 all the topics. However, on the whole, we believe 747 that the reduction to nominal terms has led to a rather clear delineation of subtopics relevant to the 748 problem of climate change. Figure 4 displays a plot 749

where (on the left-hand side) the neighborhood of topics can be studied. Notably, observe the proximity between topics 16 (*weather*) and 17 (*storm*), or the isolated position of topic 18 (*island*). The close clustering of topics 2 (*administration*), 5 (*energy*), 7 (*company*), 9 (*plant*), and 11 (*state*) appears to be significant, indicating thematic interrelations.

As a preliminary approximation, we tagged each text in the subcorpus with the predominant topic identified by the model. This enables us to visualize the development of topic coverage over time; see Figure 5. This LDA-based analysis highlights how the context of CC-related coverage in the NYTAC corpus shifts over time, for example from a framing within science and pollution debates to a discourse context in which greenhouse gas emissions were central. Adding to our manual inspection in Section 3.3 that showed how climate change can be one of many issues in longer articles about general government policy (topic "administration"), the topic modeling also indicates how CC debates may be embedded in broader discussions about foreign policy ("China") or in articles about culture and arts ("people").

## 5 Conclusion and Future Work

In this paper, we introduced the NYTAC-CC, a topic-specific subcorpus of 3,630 articles on climate change (CC) drawn from the New York Times Annotated Corpus covering the span from 1987 to 2007. This marks the first CC analysis using this data set. Our work addresses the scarcity of available news-based textual resources for climate change, crucial for many NLP downstream tasks. We constructed the corpus using a hybrid approach that combines keyword-based prefiltering with automatic classification, effectively optimizing the extraction process. The representativeness of the subcorpus is validated through the application of ClimateBERT, with classification results revealing both the model's intrinsic limitations and the topicconsistency of the subcorpus. Initial explorations, including basic statistics, keyword analysis, and topic modeling, have already highlighted the potential for nuanced diachronic analysis and more fine-grained subtopic exploration. As future work, we plan to extend these preliminary findings by employing advanced topic modeling techniques, such as structured topic modeling that systematically incorporates time and dynamic topic modeling.

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