NELA-GT-2021: A Large Multi-Labelled News Dataset for The Study of Misinformation in News Articles

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Abstract

In this paper, we present the fourth installment of the NELA-GT datasets, NELA-GT-2021. The dataset contains 1.8M articles from 367 outlets between January 1st, 2021 and December 31st, 2021. Just as in past releases of the dataset, NELA-GT-2021 includes outlet-level veracity labels from Media Bias/Fact Check and tweets embedded in collected news articles. The NELA-GT-2021 dataset can be found at: https://doi.org/10.7910/DVN/RBKVBM

1 Introduction

Across a range of disciplines, from the study of mass communication to the building of automated tools in computer science, news media data is critical to move research forward. For example, mixed-methods studies examining news coverage behaviors, such as the coverage of elections (Harmer and Southern 2019; Kawakami, Umarova, and Mustafaraj 2020) or coverage of pandemics (Krupenkin et al. 2020; Joseph et al. 2021), need historical article data for their analyses. Quantitative big data studies examining big picture behaviors, such as content sharing in fringe media (Starbird et al. 2018; Horne, Nørregaard, and Adalı 2019a), need news data that is consistent across time and covers a spectrum of outlet types. Research in automatic fact-checking and 'fake news' detection need large news datasets with veracity labels (Baly et al. 2018; Bozarth and Budak 2020; Horne, Nørregaard, and Adali 2019b).

To these many ends, researchers and practitioners have focused on creating high-quality news datasets of varying types. There are multiple platforms dedicated to collecting news data, such as Media Cloud, an open source platform used for collecting and analyzing global news coverage (Roberts et al. 2021), and LexisNexis, a commercial news database often used in academic studies (Deacon 2007).

There are also many static, one-time news data collections, particularly focused on the veracity of news. For example, the FA-KES dataset (Salem et al. 2019), the Golbeck et al. dataset (Golbeck et al. 2018), and the Election-2016 dataset (Bode et al. 2020; Bozarth and Budak 2020). Other one-time datasets focus on social media posts rather than news articles, such as the FakeNewsNet dataset (Shu et al. 2018) and the LIAR dataset (Wang 2017).

While all of these data sources have been useful for a variety of research studies, there continues to be a need for updated news data. Platforms like Media Cloud do an excellent job at capturing high-quality, current news coverage around the world, but do not capture low-veracity news outlets. Datasets like the Golbeck et al. dataset and the FA-KES datset capture low-veracity news, but quickly become outdated. The yearly-released NELA-GT datasets continue to fill both these gaps: updated news coverage across both low and high veracity outlets.

In this short paper, we describe the fourth release of the NELA-GT datasets, NELA-GT-2021. In NELA-GT-2021 we have collected **1,856,509** articles from **367** outlets between January 1st, 2021 and December 31st, 2021. Included with these news articles are outlet-level veracity labels from Media Bias Fact Check, with **348** of **367** outlets labeled, and data on **157K** distinct tweets embedded into collected news articles.

In this paper, we describe what is new in the 2021 version of the dataset, the collection process, the publicly-available data formats, and potential use cases.

2 What's New in NELA-GT-2021?

Rather than add new features to the dataset, our main goal for the 2021 collection was to stabilize our collection infrastructure to ensure complete coverage of articles published across the full year. Hence, as shown in Figure 1, we estimate that our collection has little to no missing article data in 2021.

Note that there are fewer outlets in NELA-GT-2021 than in NELA-GT-2020. This reduction is due to many small, low-veracity outlets shutting down and a few major news outlets stopping their RSS feed support, such as Reuters ¹.

3 Data Collection

3.1 News data and metadata

The data collection process follows what was described in (Nørregaard, Horne, and Adalı 2019). Specifically, we scraped the RSS feeds of each outlet in our outlet list twice a day starting on 01/01/2022 using the Python libraries feedparser and Goose3². This list of outlets to collect was carried

¹https://www.reuters.com/

²https://github.com/grangier/python-goose

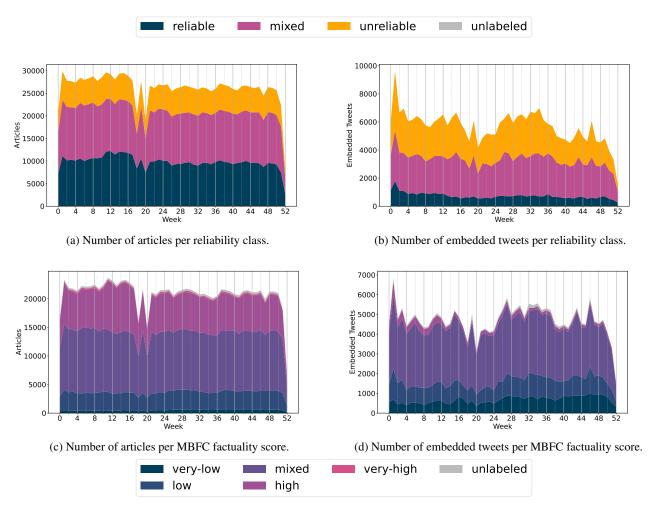


Figure 1: Number of articles (a, c) and embedded tweets (b, d) collected during each week of 2021.

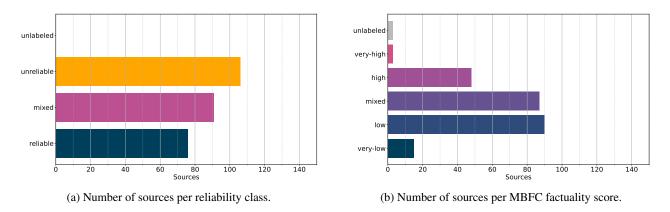


Figure 2: Distribution of sources per reliability class (a) and factuality (b) score.

over from (Gruppi, Horne, and Adalı 2021). These sources come from a variety of countries (or the country of origin is not known), but are all articles are in English.

See Table 1 for details on each attribute stored during the collection process.

3.2 Embedded tweet data

In 2020, we introduced additional data on tweets embedded into news articles (Gruppi, Horne, and Adalı 2020). We again collect this data for the 2021 dataset. Specifically, we collected embedded tweets on the article page using the Goose3 library. The ID of the embedded tweet is stored in the database table tweet, along with the id of the article from which it was collected and the text of the tweet. We show this structure in Table 2.

3.3 Limitations

Since the articles collected from news sources may be copyrighted, we apply a transformation to the original text so that it cannot be used for their originally intended purpose, i.e., that of being read by individuals to consume journalistic information.

We modify the text so that it cannot properly be used for news consumption but can still be used for text analysis by periodically removing words from the text. For articles with more than 200 tokens, we replace 7 tokens with '@' every 100 tokens. For articles with fewer than 200 tokens, we replace 5 consecutive tokens with '@' every 20 tokens. This transforms the articles so that it is unlikely that a user will read NELA-GT to consume news while still keeping most of the content that is useful for analysis (approximately 7% for larger articles).

4 Format of Data

Just as in the past two versions (2019, 2020), the dataset has been released in two formats: (1) a SQLite database, (2) a JSON dictionary per news source. Details about the structure of each of these formats is below. We provide Python code to read both data formats at: https://github.com/MELALab/nela-qt.

The SQLite 3 database schema consists of two tables: newsdata and tweet. The newsdata table contains, in each row, data about an article. Column **id** is set as primary key to avoid duplicated entries on the database. We normalized source names by converting them to lower case, and removing spaces, punctuation, and hyphens. For example, the source *The New York Times* appears as *thenewyorktimes*, Tables 1 and 2 give information about data columns.

4.1 JSON Format

We also provide the dataset in JSON format. Specifically, each source has one JSON file containing the list of all of its articles. The fields follow the same structure of the database columns (Tables 1 and 2).

4.2 Ground Truth Data Format

We include multiple types of source-level veracity labels. In NELA-GT-2021, we collect source-level labels from Me-

dia Bias/Fact Check (MBFC) that contain the following dimensions of veracity:

- 1. Media Bias Fact Check factuality score on a scale from 0 to 5 (low to high credibility).
- Media Bias Fact Check Conspiracy/Pseudoscience and questionable sources - low credibility if a source belongs to these categories.

In addition, we create an aggregated version of the factuality scores, broken down into three classes: *reliable*, *mixed*, and *unreliable*.

Due to the limited availability of veracity labels from other platforms, we choose to only collect labels from MBFC. However, we encourage researchers to use and compare veracity labels from multiple resources when possible. This is particularly important when testing machine learning models. For an overview of the impact of ground truth labels on news studies, please see (Bozarth, Saraf, and Budak 2020). Furthermore, we strongly encourage machine learning researchers to test news veracity models using robust evaluation frameworks, such as those discussed in (Bozarth and Budak 2020) and (Horne, Nørregaard, and Adali 2019b).

5 Use Cases

5.1 Analysis of news coverage during events

One of the primary goals in the yearly-release of the NELA-GT datasets is to provide updated coverage of current events. To this end, we provide two example subsets of the database for two events during 2021: the continued COVID-19 pandemic and the January 6th U.S. Capitol riots.

COVID-19 Understanding news coverage COVID-19 and COVID-19 health policies continue to be a vital research area. In 2021, the COVID-19 vaccines were a focal point of public health campaigns and media. The NELA-GT-2021 dataset allows researchers to examine vaccine messaging across both mainstream and alternative media, and in combination with other datasets can provide insights into vaccine hesitancy in online communities (Neff et al. 2021). To this end, we create a subset of the NELA-GT-2021 dataset using a set of COVID-19 keywords. This subset was generated via a simple keyword search on article title and body text. If an article had one or more keywords from our set featured in the title or body text, it was included in the COVID-19 subset. Some examples of the keywords used can be found in Table 3 and the full keyword list is included with the dataset. Figure 3a shows the number of news stories related to COVID-19 compared to all articles collected in each week of 2021.

If the 2020 and 2021 NELA-GT datasets are combined, researchers can have a near-complete view of COVID-19 news coverage.

January 6th U.S. Capitol riots Another significant event covered by the dataset is the January 6th U.S. Capitol riots. In short, on January 6th 2021, a mob of people in support of former U.S. President Donald Trump vandalized and broke into the U.S. Capitol building during the joint session

Column	Type	Description
id	text (primary key)	Article identifier.
date	text	Publication date string in YYYY-MM-DD format.
source	text	Name of the source from which the article was collected.
title	text	Headline of the article.
content	text	Body text of the article.
author	text	Author of the article (if available).
published	text	Publication date time string as provided by source (inconsistent formatting).
published_utc	integer	Publication time as unix time stamp.
collection_utc	integer	Collection time as unix time stamp.
url	Text	URL of the article.

Table 1: Structure of NELA-GT-2021 article data. For the database format, column id is the primary key of table newsdata.

Column	Type	Description
id	text (primary key)	Tweet id.
article_id	text (foreign key)	Id of the article in which the embedded tweet was observed.
embedded_tweet	text	ID/URL of the embedded tweet.

Table 2: Structure of NELA-GT-2021 embedded tweets. For the database format, column id is the primary key of table tweet.

of Congress assembled to count electoral votes. Since then, understanding the messaging before and after the event has been a focal point of researchers in communications, political science, and information science (Prabhu et al. 2021; Davidson and Kobayashi 2022; de Graaf 2021). Hence, we create a subset of the NELA-GT-2021 dataset using a set of keywords related to the Capitol riots. In Figure 3b shows the number of news stories related to the riot compared to all articles collected in each week of 2021.

Again, in combination with the 2020 NELA-GT dataset, a full picture of news coverage and messaging before the 2020 U.S. Presidential Election up to and after the January 6th Capitol riots is captured.

5.2 Embedded Tweets

By providing embedded tweets, the dataset can be used to further the already rich literature on hybrid media systems (Chadwick 2017). As coined by Chadwick, a hybrid media system is when different types of media mutually interact, such as social media and news media. Researchers are particularly interested in this in the context of political communications, where messaging from politicians can be directly embedded in news coverage.

Tweets are particularly central in this framework. Multiple studies have shown that the use of tweets embedded in news articles is common. For example, Bane (2019) provides evidence that web-only news publications frequently quoted Twitter in their articles during 2016 and 2017 (Bane 2019). Broersma and Graham (2013) showed an increase in tweets used as quotes in British and Dutch newspapers between 2007 and 2011 (Broersma and Graham 2013). Lastly, Oschatz et al. 2021 show that the frequency and function of embedded tweets in news articles can change across countries and different types of media (Oschatz, Stier, and Maier 2021).

By providing the tweets embedded in news articles, the

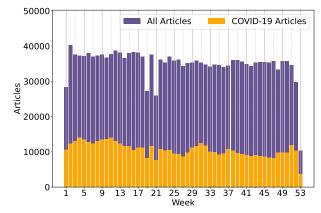
NELA-GT-2021 dataset can be useful furthering in studies of political communications and hybrid media systems. Notably, very few studies have addressed low-veracity news sources role in these hybrid systems, which this dataset can aid

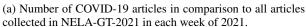
5.3 Long-Term Use Cases

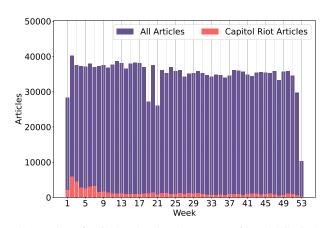
Just as discussed in (Gruppi, Horne, and Adalı 2021), one of our goals with the continued release of the NELA-GT datasets is to support long-term news research. When combining all of the NELA datasets (both the NELA-GT datasets (Nørregaard, Horne, and Adalı 2019; Gruppi, Horne, and Adalı 2020; Gruppi, Horne, and Adalı 2021) and the original NELA2017 dataset (Horne, Khedr, and Adalı 2018)), we provide over 4.4M news articles across 4.5 years. There are multiple research avenues that this data, both in part and as a whole, supports:

- Robust machine learning: This dataset allows for continued work in automated news veracity detection, particularly in robustness checks of current work. These robustness checks include examining prediction accuracy over time, over events, and over mixed veracity labels. We again encourage machine learning researchers to test news veracity models using robust evaluation frameworks, such as those discussed in (Bozarth and Budak 2020), and to use multiple datasets when possible.
- Examining media manipulation: Using the veracity labels in this dataset, research can examine tactics used by hyper-partisan news outlets. Additionally, with knowledge of media manipulation campaigns, such as those discussed in the Media Manipulation Casebook³, researchers can examine how media manipulation is propagated through malicious news outlets. While there has

³https://mediamanipulation.org/







(b) Number of articles related to the January 6th U.S. Capitol riot in comparison to all articles collected in NELA-GT-2021 in each week of 2021.

Figure 3: Number of articles related to (a) COVID-19, and number of articles related to (b) the January 6th Capitol riots as a fraction of the total number of articles in each week of 2021. Articles are found using a set of keywords shown in 3.

been a substantial focus on "fake news" detection methods by researchers, there continues to be room to better understand and characterize media manipulation and disinformation campaigns and tactics.

Exploring event-driven dynamics of and narratives in news media: Quantitative and qualitative analyses of narrative themes before, during, and after major events continues to be a useful methodology in interdisciplinary media studies. This dataset supports these works by maintaining consistent data collection across events.

Conclusion

In this paper, we describe the NELA-GT-2021, a dataset of news articles from sources of varying veracity. The RSS feeds from the sources were scraped twice a day on every day of 2021, resulting in a set with 1.8M articles from 367 outlets. The dataset includes the source factuality labels from Media Bias Fact Check and tweets that were embedded in the collected news articles. We provide two eventbased subsets of the dataset for the study of news coverage and messaging around COVID-19 and the January 6th U.S. Capitol riots. These subsets were generated from the original dataset by filtering articles based on keyword matching.

The dataset and additional documentation can be found at: https://doi.org/10.7910/DVN/RBKVBM. Example code for data extraction can be found at: https: //github.com/MELALab/nela-gt.

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COVID-19 keywords | January 6th keywords

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pandemic	capitol riot
airborne transmission	January 6th
anti mask	stop the steal
anti-lockdown	insurrection
anti-mask	election fraud
antibodies	voter fraud
cdc	
contact tracer	
corona virus	
coronavirus	
covid	
covid-19	
distance learning	
face covering	
face mask	
fauci	
lockdown	
plandemic	

Table 3: Examples of keywords used to make the eventbased data subsets for COVID-19 and the January 6th U.S. Capitol riots. The full keyword lists are provided with the dataset.

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