EDNA-Covid: A Large-Scale Covid-19 Tweets Dataset
Collected with the EDNA Streaming Toolkit

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ABSTRACT
The Covid-19 pandemic has fundamentally altered many facets of our lives. With nationwide lockdowns and stay-at-home advisories, conversations about the pandemic have naturally moved to social networks, e.g. Twitter. This affords an unprecedented insight into the evolution of social discourse in the presence of a long-running destabilizing factor such as a pandemic with the high-volume, high-velocity, high-noise Covid-19 Twitter feed. However, real-time information extraction from such a data stream requires a fault-tolerant streaming infrastructure to perform the non-trivial integration of heterogeneous data sources from news organizations, social feeds, and authoritative medical organizations like the CDC. To address this, we present (i) the EDNA streaming toolkit for consuming and processing streaming data, and (ii) EDNA-Covid, a multilingual, large-scale dataset of COVID-19 tweets collected with EDNA since January 25, 2020. EDNA-Covid includes, at time of this publication, over 600M tweets from around the world in over 10 languages. We release both the EDNA toolkit and the EDNA-Covid dataset to the public so that they can be used to extract valuable insights on this extraordinary social event.

1 INTRODUCTION
Covid-19, also known as the 2019 Novel Coronavirus disease, is caused by the SARS-CoV-2 virus. It is a rapidly spreading disease that was first reported in Wuhan, China, in December 2019, and has since spread to all continents across the globe. It was first picked up as a viral pneumonia in the Wuhan region on December 31, 2019. WHO signaled the agency’s highest level of alarm on January 30, 2020, by labeling the outbreak as a Public Health Emergency of International Concern, and subsequently declared it a pandemic on March 11, 2020 after reports of 118K cases in 114 countries and a 13x increase in cases outside China within 2 weeks.

Since then, over 33M people have contracted the disease, with over 1M fatalities and 24M recoveries, as of September 30, 2020. The response to the pandemic has run the gamut, from complete nationwide lockdown with strict enforcement, as in the case of China and several Western European nations like Italy, France, and Spain, to stay-at-home advisories with decentralized enforcement in the United States, to no lockdown combined with extensive testing and contact tracing, in South Korea, to no lockdown with no federal contact tracing.

In conjunction, both WHO and national CDCs have both recommended a slew of guidelines to slow down the spread and flatten the curve to ensure the healthcare industry is not strained with surge in infections. These guidelines, which include public mask mandates, social distancing, work-from-home, cancellation of public events, and shutdown of schools, have naturally led to increasing online participation as people turn to social media to carry out the conversation.

This sustained increase in online engagement in reference to a single event provides an unprecedented insight into a slew of areas in natural language processing, such as social communication modeling, credibility analysis, topic modeling, and fake news detection. Our EDNA-Covid dataset, which contains over 600M tweets from over 10 languages, would be an excellent source for research into the social and language dynamics of the pandemic. Our dataset demonstrates concept drift (see Figure 5 in subsection 3.3), making it ideal for testing streaming models of analytics.

Data exhibits concept drift when its underlying distribution changes over time, usually over several years. Under concept drift, machine learning models and conventional offline analytics will degrade as their prediction data desynchronized from their training data model. Concept drift is a natural part of real data; several examples of drift abound in nature, from changing seasons [15], which can degrade performance of computer vision systems, to lexical drift [8], which can degrade performance of NLP models over different geographical regions. An important requirement in concept drift research is data that exhibits such drift to enable development and testing of drift detection and adaptation mechanisms.

With EDNA-Covid, we present a dataset that exhibits concept drift. The online discourse on the Covid-19 pandemic has taken root in a dizzying array of online communities, such as sports [12], academia [18], and politics [1]. This allows us a firsthand look at a real-world example of concept drift as the online conversations change over time to accommodate new actors, knowledge, and communities. This yields a high-volume, high-velocity data stream with noise and drift as the underlying conversations about the pandemic transition from confusion to information to misinformation [5] and today, with the US election nearing, disinformation [11].

We will first present EDNA, our toolkit for consuming and processing streaming data. Then we present EDNA-Covid dataset, the streaming methods we employed, and some salient statistics about the dataset.

2 EDNA
EDNA is an end-to-end streaming toolkit for ingesting, processing, and emitting streaming data. EDNA is based on our prior work with LITMUS [14] and ASSED [16], and incorporates a slew of improvements for faster deployment, fault tolerance, and end-to-end management. EDNA’s initial use was a test-bed for studying concept drift detection and recovery. Over time, it has grown to a toolkit...
for stream analytics. We are continuing to work on it to mature it for production clusters. We have released an alpha version at https://github.com/asuprem/edna. In this section, we describe some high-level details about the toolkit.

2.1 Architecture

The central abstraction in EDNA is the ingest-process-emit loop, implemented in an EDNA Job. We show an EDNA Job in Figure 1. EDNA Job. Each component of the loop in an EDNA Job is an abstract primitive in EDNA that is extended to create powerful operators.

1. Ingest primitives consume streaming records.
2. Process primitives implement common streaming transformations such as map and filter [2]. Multiple process primitives can be chained in the same job.
3. Emit primitives generate an output stream that can be sent to a storage sink, such as a SQL table, or to another EDNA Job.

EDNA Application. An EDNA Application consists of several jobs in a DAG, as in Figure 2. We apply the EDNA Job abstraction to the application as well, where an EDNA Application consists of:

1. At least 1 Ingest-Job to ingest a stream from external sources, such as the Twitter Streaming API. The Ingest-Job should not do any processing to reduce backpressure and ensure the highest throughput for consuming an external stream.
2. Process-Jobs that process the stream. Each Process-Job runs its own ingest-process-emit loop to transform the stream.
3. At least 1 Emit-Job to emit a stream to external sinks, such as a SQL table, S3 bucket, or distributed file system such as Hadoop.

2.2 The EDNA Stack

The EDNA stack (Figure 3) consists of four layers: deployment, runtime, APIs, and plugins.

EDNA can be deployed on a local machine for single jobs or on clusters managed by orchestrators like Kubernetes for multiple jobs in a streaming application. On a cluster deployment, EDNA uses Apache Kafka [19], a durable message broker with built-in stream playback to connect jobs, and Redis [3] to share information between jobs. The EDNA runtime manages and executes jobs on the applied deployment. EDNA Jobs use the ingest, process, and emit APIs to implement the ingest-process-emit loop, with the appropriate plugin for complete the job.

The next section describes our EDNA-COVID dataset and the EDNA Application we use to generate the dataset.

3 EDNA-COVID DATASET

We have collected the EDNA-COVID dataset since January 25, 2020 using Twitter’s streaming API. Over time, we have also enriched our dataset with other similar datasets, such as [4] and [13]. EDNA-COVID is similar in scale to [4]; in addition, we also provide our dataset with other similar datasets, such as [4] and [13]. EDNACOVID is an order of magnitude larger than [13], with over 60M tweets between January and March 2020, compared to 6M for [13].

3.1 EDNA Application

We show our EDNA Application to stream tweets for the EDNA-COVID dataset in Figure 4. It consists of the following jobs:

• Twitter Ingest: This job connects to the Twitter v2 sampled stream endpoint and consumes records for the application. We use the Twitter Sampled Stream API, available at [17]. This API provides a real-time stream of 1% of all tweets.
• Archive: We immediately archive the raw objects to disk.
• Metadata extractor: This job extracts the tweet object from the streaming record and performs some data cleaning in discarding malformed, empty, or irrelevant tweets. Tweets are kept if they contain coronavirus related keywords: coronavirus, covid-19, ncov-19, pandemic, mask, wuhan, and virus. To capture Chinese social data, we also include these keywords in Mandarin. We initially included the keyword china during data collection in January and February, but decided to omit the phrase since it introduced significant noise, and any tweets with the keyword that were relevant to coronavirus already include the above keywords.
3.2 Dataset description

Even with 1% of the Twitter stream, we are able to collect a large-scale dataset of tweets. We show in Table 1 the tweets collected since January. We converted to parallelized Metadata Extractor jobs near the end of June to improve our data collection and reduce instances of dropped tweets. We also updated our keyword filtering approach to keep tweets that are retweets of matching tweets.

| Month   | No. Tweets |
|---------|------------|
| 2020-01 | 8,714,684  |
| 2020-02 | 25,553,003 |
| 2020-03 | 31,564,785 |
| 2020-04 | 25,498,020 |
| 2020-05 | 26,895,960 |
| 2020-06 | 99,415,221 |
| 2020-07 | 112,215,578|
| 2020-08 | 113,543,567|
| 2020-09 | 103,454,256|

Our data is skewed towards English language tweets, as we show in Table 2 with the top 5 language categories. We also included Chinese and Japanese tweets with keywords in the corresponding languages; including Chinese keywords nets us ~25K tweets per month, which is less than 0.1% of the collected tweets, and including Japanese keywords adds ~50K tweets per month. This includes enrichment with tweets from [4, 13].

| Language                  | No. Tweets | Pct Total |
|---------------------------|------------|-----------|
| English                   | 395,109,343| 63.4%     |
| Spanish                   | 76,653,705 | 12.3%     |
| South Asian (Indonesian, Javan, Malay) | 23,681,633 | 3.8%     |
| French                    | 21,812,030 | 3.5%     |
| Portuguese                | 19,942,427 | 3.2%     |
3.3 Concept Drift in EDNA-Covid

Since EDNA-COVID is a real-time, multilingual stream of a current event, it is ideal for studying concept drift. We show an example of drift in Figure 5, which displays the fraction of the stream that matches our keywords. Initially, wuhan is a strong keyword for the stream, since the origin was an important topic of discussion. Coronavirus plus related keywords (covid, ncov) grew in importance from the end of January, when WHO declared a global health emergency. A sharp increase follows from February 11, when WHO formally names the disease caused by the virus as Covid-19. Pandemic enters the stream on February 21, when WHO reported it was preparing for the eventuality, and begins climbing on March 11, the date of the pandemic declaration.

In addition, conversations about wuhan peak in the first few weeks and then decline, signifying the shift in conversations towards the disease itself. More recently, conversations about the pandemic itself have taken precedence over conversations about the disease, as pandemic and mask see increased weight in the stream. As masks have become a more contentious issue, there has been a resurgence in conversations about masks, necessitating adjustments to data collection, cleaning, and misinformation detection starting July, 2020.

3.4 Dataset release

Due to Twitter TOS regarding release of tweets, we are releasing only the Tweet IDs of the dataset to the public through a registration method. We have provided a form at https://forms.gle/dFfYhuMzyPMunY17H9 for dataset requests. We will then provide Tweet IDs of our collected tweets. Tweet IDs need to be hydrated first using tools like twarc [7]. We have also provided a sample of TweetIDs for the first few months at https://github.com/asuprem/EDNA-Covid-Tweets.

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