corpus_exploration_and_cleaning

November 25, 2025

[1]:
```python
%reload_ext autoreload
%autoreload 2

from pathlib import Path
import sys

from dotenv import load_dotenv

# climb up until we hit the repo root, then add src
here = Path.cwd().resolve()
while here.name != "over-intra-news" and here.parent != here:
    here = here.parent

src_path = here / "src"
if str(src_path) not in sys.path:
    sys.path.insert(0, str(src_path))

load_dotenv()
```

[1]:
```
True
```

1 1 Corpus exploration, cleaning, and LDA-ready news dataset

1.1 1.1 Background and motivation

The news parser pipeline ingests CC-NEWS WARC samples from S3 and produces a `parsed_news_articles` warehouse table keyed by `(article_id, trading_day, session)`. For each WARC response, the parser applies a sequence of strict gates:

- HTTP status must be 200 and `Content-Type` must contain `text/html`.
- The HTML payload is decoded into Unicode, reduced to visible ASCII text, and required to have at least 25 tokens and at most `MAXIMUM_ALLOWED_TOKENS`.
- Language detection via `langdetect.detect_langs` must identify English as the top language with probability at least `LANGUAGE_ACCEPTANCE_PROBABILITY`.
- Canonicalized article tokens must match between 1 and 3 firms in the S&P 500 universe, using high-precision name-part matching rules.

Records that pass all gates are normalized into uppercase ASCII article bodies and written downstream as `ArticleData` objects, together with firm CIKs, word counts, and a scalar `language_confidence` score. These are then materialized into the `parsed_news_articles` table via the loader utilities.

This design intentionally favors precision at the parser stage, but it still admits several classes of noise that matter for topic modeling:

- Paywalls, "out-of-free-articles" stubs, and subscription gates that technically look like English HTML pages.
- Boilerplate investor-relations or syndicated press-release footers attached to otherwise valid articles.
- Navigation fragments, social-media widgets, and other CMS chrome that leak into the extracted body text.
- Non-english articles that passed the lang_detect gate (as lang_detect is stochastic).

To construct an LDA-ready corpus, the notebook adds a second layer of post-parsing filters on top of `parsed_news_articles`:

1. **Strong English filter.**
   only articles with `language_confidence` at least `STRONG_ENGLISH_CONFIDENCE_THRESHOLD = 0.999996` are retained. This tight cutoff is based on manual inspection of near-threshold articles: even at 0.999994 occasional Spanish articles slipped through, so a more conservative threshold is justified.

2. **Boilerplate prefix filter (`NOISY_PREFIXES`).**
   Articles whose `full_text` begins with known non-article prefixes are dropped entirely. These prefixes include:

   - Ticker/price tables and delayed-quote grids.
   - Subscription walls and "please log in / subscribe to continue reading" stubs.
   - Email-capture prompts and standalone disclaimers.
   - Captcha/error pages and "404 not found" responses that survive the HTML gate.

3. **Noisy substring filter (`NOISY_SUBSTRINGS`).**
   Articles containing characteristic boilerplate substrings are removed, e.g.:

   - Inline "ADVERTISEMENT" blocks and sponsored-content labels.
   - "READ MORE / RELATED ARTICLES" link farms injected mid-article.
   - Syndication and wire-service boilerplate such as "THIS STORY WAS GENERATED BY AUTOMATED INSIGHTS" or "DISTRIBUTED BY PUBLIC, UNEDITED".
   - Copyright blocks and "ALL RIGHTS RESERVED" footers.
   - Social-media widgets such as "SHARE THIS ARTICLE" or "FOLLOW US ON …".

These post-parser gates are deliberately conservative: they are designed to sacrifice recall in exchange for a high-precision core corpus that looks like genuine firm-specific news when inspected manually. The resulting article ID set serves as the **baseline training corpus for the first LDA iteration**.

Subsequent sections of the notebook:

- materialize this filtered article set back into a DataFrame via SQL;
- apply standard NLP pre-processing (tokenization, stop-word removal, vocabulary construction); and
- Ingest the processed data into a table to be ready for LDA modeling.

If diagnostics suggest unstable or noisy topics, subsequent iterations will be performed. These will tighten noise patterns or add additional gates, but this notebook defines the first rigorously filtered, LDA-ready news dataset derived from the CC-NEWS pipeline.

```
[ ]: import datetime as dt
     from infra.logging.infra_logger import InfraLogger, initialize_logger
     from notebooks_utils.data_notebooks_utils.corpus_exploration_and_cleaning_utils.
      ↪corpus_exploration_and_cleaning_utils import sample_corpus_per_day
     start_date = dt.date(2016, 8, 1)
     end_date = dt.date(2025, 8, 1)
     logger: InfraLogger =␣
      ↪initialize_logger("corpus_exploration_and_cleaning_utils_sample_corpus_per_day",␣
      ↪"INFO")

     # For logging to appear change the log level to DEBUG.
     # This is a No-OP if real_run is not set to TRUE.
     sample_id_set = sample_corpus_per_day(start_date, end_date, logger)
```

1.1.1 1.2 Temporal coverage of filtered articles and CIKs

Before constructing an LDA design matrix, the temporal coverage of the cleaned news corpus is examined over the full sampling window from 2016-08-01 through 2025-08-01. All diagnostics in this section are based on the **filtered article set** obtained from `parsed_news_articles` after applying:

- the parser-level gates described in Section 1.1 (HTTP status, HTML decoding, length, language, and firm-match filters), and
- the post-parser strong-English and boilerplate filters (`STRONG_ENGLISH_CONFIDENCE_THRESHOLD`, `NOISY_PREFIXES`, `NOISY_SUBSTRINGS`).

The first set of plots reports the **number of retained articles per trading day**, separately for the overnight and intraday sessions and then for both sessions combined. These time series provide a visual check that:

- coverage is non-degenerate across the sample (no long stretches with zero articles),
- major shifts in CC-NEWS availability or parser behavior are detectable as level shifts, and
- the relative density of overnight vs. intraday news is understood before constructing session-specific signals.

The second set of plots summarizes **firm-level news support**. Using the CIK lists attached to each article, the diagnostics report, for each CIK:

- the total number of articles mentioning the firm;
- the number of unique trading days with at least one article;
- the number of unique months with at least one article; and
- the number of unique years with at least one article.

These histograms quantify how evenly the cleaned corpus is distributed across firms and over time. In particular, they highlight sparsely covered CIKs whose topic exposures would be poorly estimated, and they inform later decisions about restricting the tradable universe or imposing minimum-coverage thresholds prior to LDA training and return-prediction regressions.

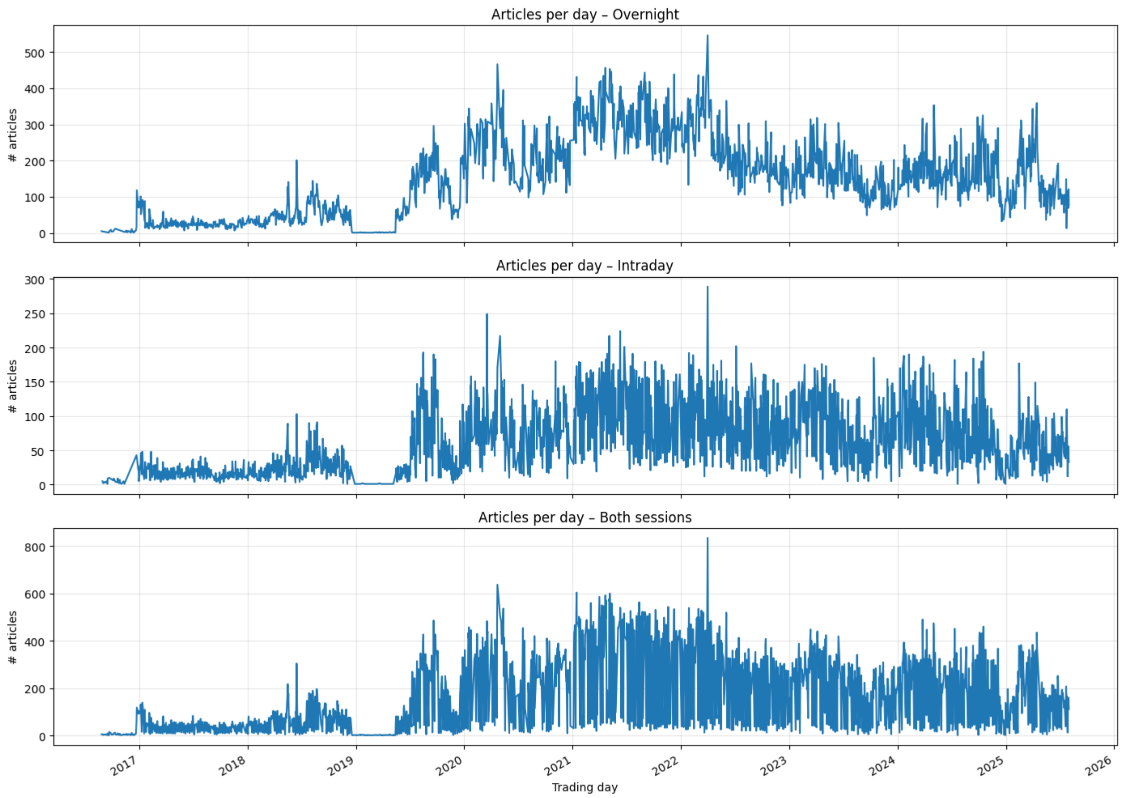
Note — resource usage

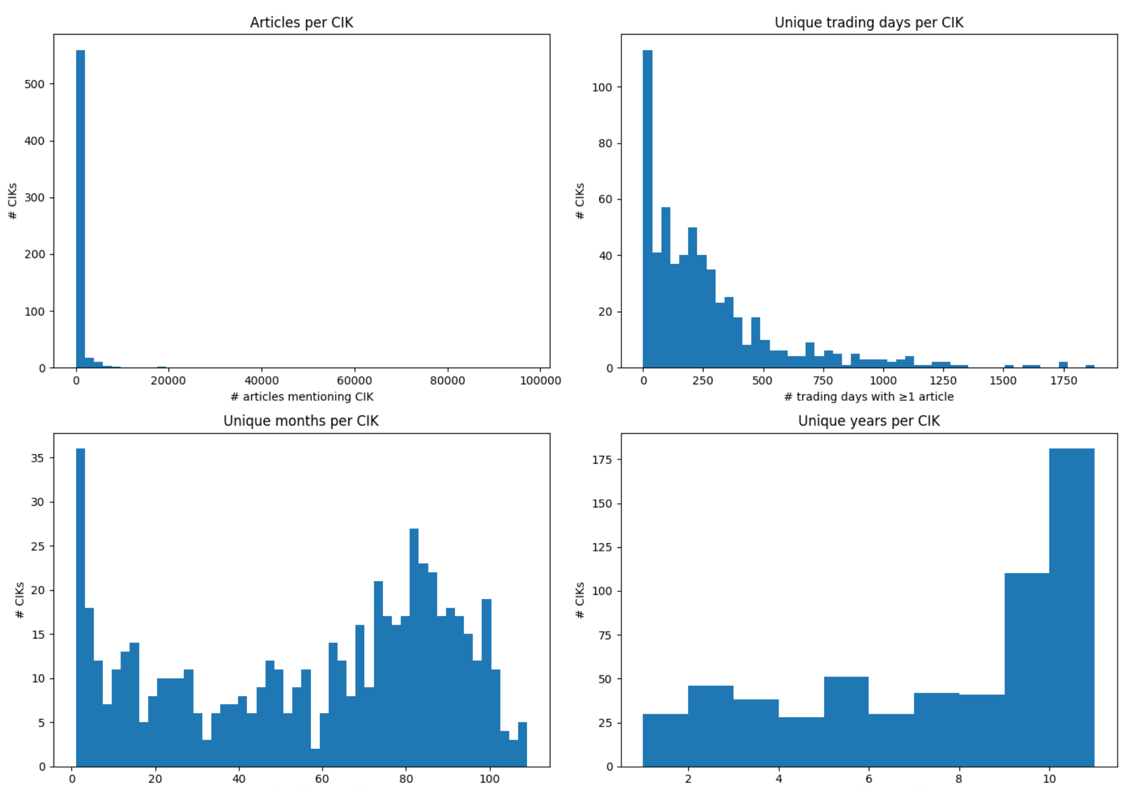
Loading the filtered article sample into `filtered_sample_df` is memory-intensive: on the reference machine used to develop this notebook, it occupies roughly **5–6 GB** of RAM.

[3]:
```
import pandas as pd
from notebooks_utils.data_notebooks_utils.general_data_notebooks_utils import␣
↪connect_with_sqlalchemy
article_sample_query: str = """
    SELECT *
    FROM parsed_news_articles
    WHERE article_id = ANY(%(samples)s)
"""
engine = connect_with_sqlalchemy()
filtered_sample_df: pd.DataFrame = pd.read_sql(
    article_sample_query,
    engine,
    params={"samples": list(sample_id_set)},
).drop_duplicates(subset=["full_text"])
```

[4]:
```
from notebooks_utils.data_notebooks_utils.corpus_exploration_and_cleaning_utils.
↪corpus_exploration_and_cleaning_plotting import (
    plot_article_temporal_and_cik_coverage
)

plot_article_temporal_and_cik_coverage(filtered_sample_df)
```


Articles per day – Overnight
articles
Articles per day – Intraday
articles
Articles per day – Both sessions
articles
2017
2018
2019
2020
2021
2022
2023
2024
2025
2026
Trading day


Articles per CIK
CIKs
articles mentioning CIK
Unique trading days per CIK
CIKs
trading days with ≥1 article
Unique months per CIK
CIKs
months with ≥1 article
Unique years per CIK
CIKs
years with ≥1 article

1.2 1.3 Interim assessment of coverage and implications for LDA

1.2.1 1.3.1 Article-level coverage

The article-per-day plots indicate that, after the parser and post-parser filters are applied, news coverage is reasonably dense over the full sample and particularly stable from 2020 onward. Overnight and intraday sessions each exhibit on the order of a few hundred retained articles per trading day, with:

- no extended runs of zero coverage;
- only a small number of visible level shifts; and
- broadly stable behavior in the 2020–2025 subperiod.

This pattern suggests that, at least in the later years, both sessions provide a sufficiently rich stream of firm-specific news for topic modeling and return-prediction work.

1.2.2 1.3.2 Firm-level coverage

The firm-level histograms reveal a more heterogeneous picture. A non-trivial set of CIKs is only lightly covered, but:

- most firms have at least one filtered article over the sample;
- most firms have at least one year with a retained article; and
- a sizable subset of firms has dozens of months and hundreds of trading days with coverage.

The month and year distributions, in particular, indicate that many CIKs enjoy sustained news flow throughout much of the 2016–2025 window, while a long tail of sparsely covered firms would yield poorly estimated topic exposures.

1.2.3 1.3.3 Implications for LDA training and regressions

In light of these diagnostics, the initial LDA model will be trained on the **full filtered corpus** from `2016-08-01` through `2025-08-01`. Early articles are thus allowed to contribute information about the latent topic structure, even in periods where coverage is relatively thin.

When constructing topic-exposure time series and running return regressions:

- attention will be restricted to dates and firms with **adequate news support**, rather than estimating exposures from a single article in an otherwise empty year; and
- coverage diagnostics will be monitored for systematic instabilities, especially in the pre-2020 period.

If topic exposures are found to be unstable or unreliable before 2020, a second iteration may be run in which the LDA training corpus is restricted to 2020 onward, and the resulting exposures compared against the baseline specification.

1.2.4 1.3.4 Motivation for validity-window-normalized coverage

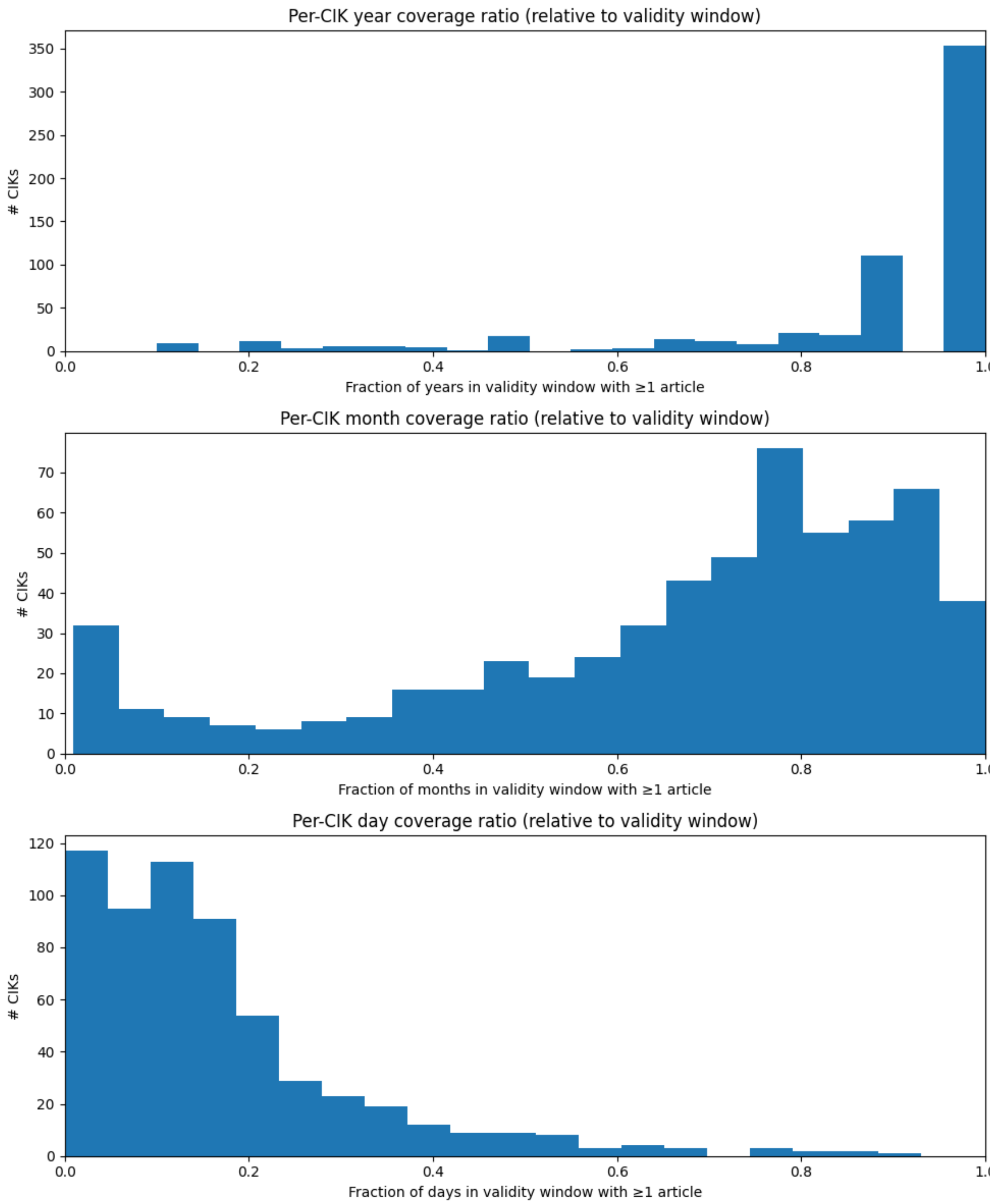
The next subsection examines coverage **relative to each firm's validity window**. For every CIK, the following window-normalized coverage ratios will be computed:

- the fraction of years in its validity window with at least one filtered article;
- the fraction of months in its validity window with at least one filtered article; and
- the fraction of trading days in its validity window with at least one filtered article.

These quantities provide a quantitative basis for defining minimum-coverage thresholds and for selecting a tradable universe that is well supported by the cleaned news corpus. At this stage, coverage is aggregated across sessions; session-specific coverage can be introduced later if required by the modeling design.

[5]:
```python
import sqlalchemy as sa
from notebooks_utils.data_notebooks_utils.corpus_exploration_and_cleaning_utils.
↪corpus_exploration_and_cleaning_plotting import (
    compute_coverage, plot_window_normalized_coverage
)
article_sample_query: str = """
    SELECT cik, validity_window
    FROM ticker_cik_mapping
    WHERE cik = ANY(%(samples)s)
"""

engine: sa.Engine = connect_with_sqlalchemy()
cik_window_df: pd.DataFrame = pd.read_sql(
    article_sample_query,
    engine,
    params={"samples": list(filtered_sample_df['cik_list'].explode().unique())},
)
coverage_df: pd.DataFrame = compute_coverage(filtered_sample_df, cik_window_df)
plot_window_normalized_coverage(coverage_df)
```



1.2.5 1.4 Validity-window-normalized coverage and remaining universe

The validity-window-normalized coverage ratios translate the raw article counts into fractions of each firm's active life that are actually supported by filtered news. For every CIK with at least one retained article, coverage is measured as the fraction of:

- years in its validity window that contain at least one filtered article;

- months in its validity window that contain at least one filtered article; and
- trading days in its validity window that contain at least one filtered article.

Across the 597 CIKs with at least one article in their validity window and the 363,280 retained articles in the corpus, the resulting histograms indicate:

- **Year-level coverage.** More than 350 firms have a year-coverage ratio of 1.0, meaning that every year in their validity window contains at least one filtered article. Only a relatively small subset of firms has materially lower year-level coverage, so for a large portion of the universe topic exposures can be treated as being supported throughout the full episode.
- **Month-level coverage.** The month-coverage histogram is strongly right-skewed. A large majority of firms have at least half of their months covered by news (coverage ratio 0.5), and many firms sit near the upper tail with coverage ratios close to 1.0. This suggests that, conditional on being in the tradable universe, most firms exhibit sustained, month-to-month news flow.
- **Day-level coverage.** Day-coverage ratios are considerably sparser. For most firms, fewer than one fifth of the trading days in their validity window have a filtered article attached. Daily topic exposures will therefore be noisy unless some temporal smoothing or pooling is applied, especially for firms with thin coverage.

In line with the design choices outlined in Sections 1.2 and 1.3, the first LDA iteration will include all 597 CIKs that have at least one filtered article within their validity window, allowing every such firm to contribute to the estimation of the latent topic structure. When constructing topic-exposure time series and return-prediction regressions, firms and periods whose exposures appear unstable or structurally under-supported can then be dropped or down-weighted based on these coverage ratios.

The next section turns to the NLP processing required to convert the 363,280 filtered article bodies into an LDA-ready corpus: tokenization, normalization, stop-word, vocabulary construction, and the creation of a sparse document–term representation suitable for topic modeling.

2 2 Canonicalization and tokenization

The coverage diagnostics in Section 1 show that, after parser and post-parser filters, the corpus consists of several hundred thousand filtered article bodies covering a broad cross-section of firms. The next step is to convert these articles into an LDA-ready representation by applying a simple, deterministic tokenization and canonicalization pipeline. This section describes what that pipeline does and what the resulting token- and document-frequency distributions look like.

2.1 2.1 Canonicalization and tokenization pipeline

Starting from the filtered article set, we apply a batch preprocessing routine that operates on the articles in chunks and maps each article body into a sequence of canonical tokens.

At a high level, the pipeline performs the following transformations:

- The article text is normalized: non-alphanumeric characters and obvious markup are stripped, punctuation is removed, and whitespace is collapsed. The normalized text is then split into word-like tokens, so that each token can be associated with a specific article identifier.

- Each token is classified as alphabetic, numeric, or alphanumeric. Purely alphabetic tokens are kept in word form; purely numeric tokens are grouped into a small number of magnitude buckets (ordinary numbers, million-scale numbers, and billion-scale numbers) so that the model retains information about scale without carrying around an unbounded vocabulary of raw numerals.
- Mixed alphanumeric strings (for example IDs, codes, or ticker-like patterns with digits) are simplified by removing their numeric component and retaining only the alphabetic part. This strips off noisy numeric suffixes while keeping the underlying word fragments that may carry meaning.
- The remaining alphabetic material is lower-cased and stemmed using an English stemmer. At the same time, a standard English stop-word list is stemmed in the same way, and any token whose stem lies in that list is removed. Very short stems and stems that still contain digits are also discarded. The result is a set of relatively clean, canonical token stems that are both compact and interpretable.

After these transformations, each article is represented as a collection of canonical tokens linked to its article identifier. These `(article_id, stemmed_token)` pairs are written out as partitioned Parquet files under a dedicated directory, providing a disk-backed, canonicalized corpus that subsequent stages can use to construct the sparse document–term matrix for LDA.

> **Note — resource usage**
>
> Running `batch_canonicalize_and_tokenize_corpus` is intentionally CPU- and I/O-intensive. In earlier versions, materializing the fully canonicalized corpus as a single in-memory DataFrame consumed on the order of **22 GB** of RAM on a standard laptop. To avoid this, the pipeline:
>
> - processes the filtered articles in chunks of size `CHUNK_SIZE`, and
> - writes each chunk directly to disk as `tokenized_parquet/tokenized_corpus_chunk_<k>.parquet` instead of returning one giant DataFrame.
>
> If the run is too heavy for your machine, you can:
>
> - **Lower `CHUNK_SIZE`** to reduce peak memory usage (at the cost of more, smaller Parquet files); and
> - **Use `resume_index`** to restart a run from the next chunk after the last file you already have. For example, if the last successfully written file is `tokenized_corpus_chunk_5.parquet`, you can rerun the pipeline with `resume_index=5` to continue from chunk 6 instead of starting over.
>
> These controls let you trade off runtime and disk usage against memory pressure so the canonicalization step can be executed safely on more modest hardware.

2.2 2.2 Token and document frequency diagnostics

Once the canonicalized corpus has been written to disk, we aggregate across all partitioned files to construct two empirical distributions:

- a global term-frequency distribution, recording the total number of occurrences of each token in the entire corpus; and
- a document-frequency distribution, recording in how many distinct articles each token appears.

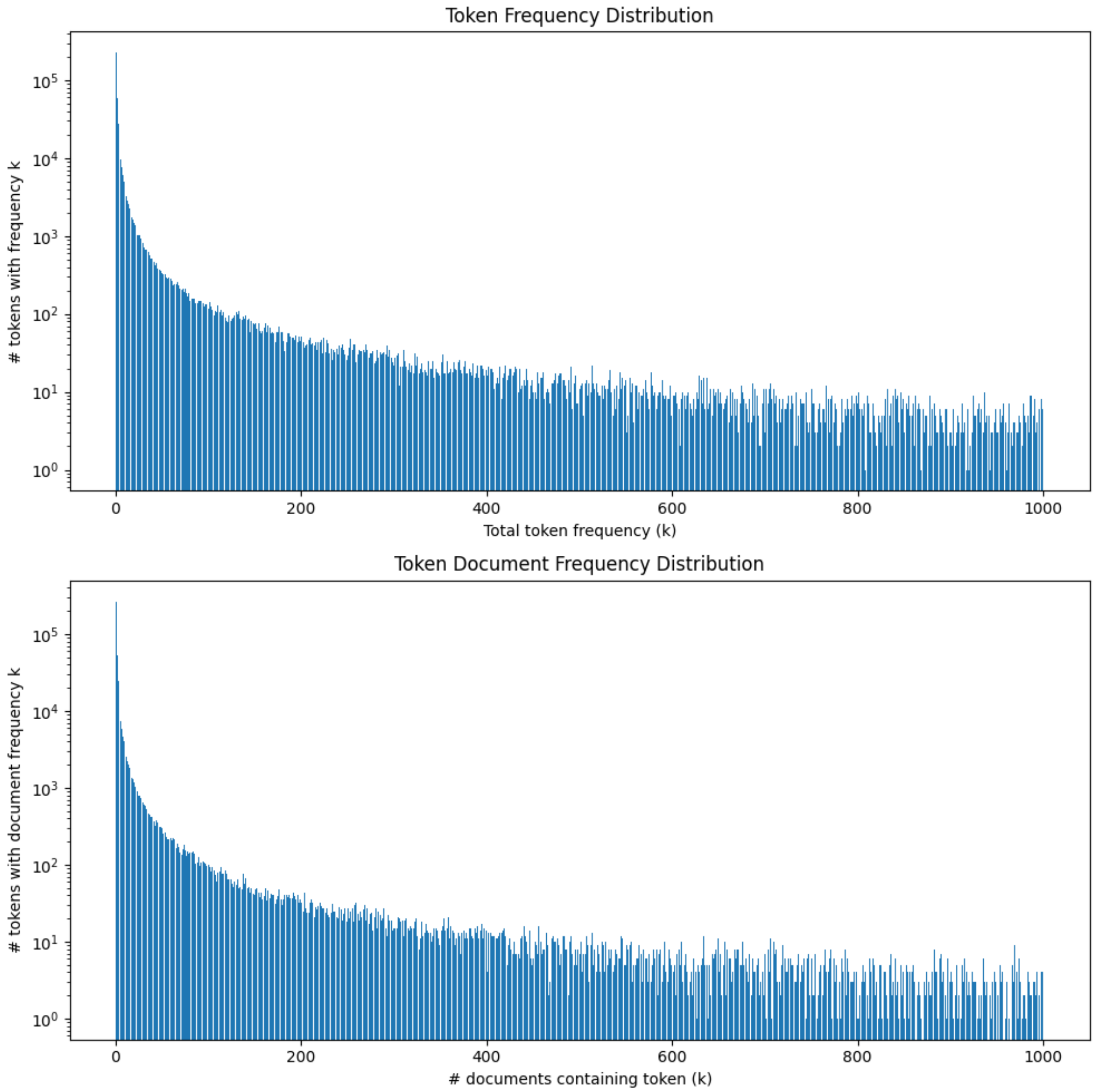
To make these distributions interpretable, the notebook converts them into "counts-of-counts" histograms. For each integer frequency level k, we count how many distinct tokens occur exactly k times in the corpus, and how many tokens appear in exactly k articles. These histograms are plotted in two panels, with the y-axis on a logarithmic scale. For readability, the x-axis in both panels is truncated at a frequency of 1,000; the underlying counters still track the full range of values, but the visualization focuses on the part of the distribution where most tokens lie.

In these plots, a large mass of tokens lies very close to zero on the x-axis: most canonical tokens appear only a handful of times in the entire corpus or in only a few articles. In other words, a high proportion of the vocabulary is densely packed near the origin. As we move to the right, the empirical density of tokens becomes progressively sparser. On the log-scaled y-axis, the counts of tokens fall off roughly monotonically with frequency, and only a small subset of words reaches the high end of the truncated range.

This heavy-tailed pattern is exactly what one would expect from a large, canonicalized news corpus. It confirms that the preprocessing pipeline has produced a vocabulary in which most items are rare or moderately frequent (and thus potentially informative for firm- and context-specific topics), while a relatively small number of very common tokens can be handled later through explicit vocabulary pruning or additional stop-wording. These diagnostics provide a quantitative baseline for setting minimum and maximum frequency thresholds before constructing the final sparse document–term representation for LDA training.

[6]:
```python
from notebooks_utils.data_notebooks_utils.corpus_exploration_and_cleaning_utils.
 ↪corpus_exploration_and_cleaning_utils import (
    FrequencyCounters,
    batch_canonicalize_and_tokenize_corpus,
    extract_token_distributions
)
from notebooks_utils.data_notebooks_utils.corpus_exploration_and_cleaning_utils.
 ↪corpus_exploration_and_cleaning_plotting import (
    plot_token_and_doc_frequency
)

# For logging to appear change the log level to DEBUG.
# This is a No-OP unless real_run=True.
batch_canonicalize_and_tokenize_corpus(filtered_sample_df, logger)
frequency_counters: FrequencyCounters = extract_token_distributions()
plot_token_and_doc_frequency(frequency_counters.token_frequency_counter,␣
 ↪frequency_counters.token_document_counter)
```



2.3 2.3 Vocabulary pruning and rare-term filter

The canonicalized corpus provides, for each token, both a global term count (total number of occurrences across all articles) and a document frequency (number of distinct articles in which the token appears). Before constructing the final LDA inputs, we apply a simple rare-term filter and inspect the resulting vocabularies.

The rare-term filter is defined at the document level. Tokens that appear in fewer than 25 articles are dropped from the active vocabulary. For a corpus of this size, this threshold removes extremely idiosyncratic words that are unlikely to support stable topics, while retaining tokens that recur with at least minimal regularity across the news stream.

Concretely:

- We compute the size of the vocabulary **before** pruning (number of distinct canonical tokens in the corpus).

- We apply the document-frequency threshold (document_frequency 25) and record the vocabulary size **after** pruning.
- We measure how much token mass is removed by this step: both in terms of the fraction of vocabulary types dropped and the fraction of total token occurrences they represent.

As a diagnostic sanity check, we also examine the most frequent tokens in the corpus (e.g., the top 10–20 tokens by global term count and by document frequency). The goal is to verify that:

- the highest-frequency items look like genuine news vocabulary and not artifacts of the parsing pipeline; and
- any residual boilerplate terms that escaped earlier cleaning can be flagged for potential exclusion (for example, by marking them inactive in the vocabulary table).

The main effect of this stage is to define an **active vocabulary**: the set of tokens that pass the document-frequency filter and are candidates for inclusion in LDA training.

2.4 2.4 From canonicalized corpus to LDA tables

Once the active vocabulary has been identified, the canonicalized corpus is mapped into three SQL tables that together define the LDA input:

1. a per-article document view;
2. a versioned vocabulary with frequency statistics; and
3. a sparse document–term matrix linking the two.

These tables are implemented as:

```sql
-- Cleaned per-article documents
CREATE TABLE lda_documents (
    article_id          TEXT,
    corpus_version      SMALLINT NOT NULL,
    included_in_training BOOLEAN NOT NULL DEFAULT TRUE,
    token_count         INTEGER NOT NULL,
    unique_token_count  INTEGER NOT NULL,
    created_at          TIMESTAMPTZ NOT NULL DEFAULT NOW(),
    PRIMARY KEY (article_id, corpus_version)
);

-- Global vocabulary with per-token statistics
CREATE TABLE lda_vocabulary (
    term_id             SERIAL PRIMARY KEY,
    token               TEXT NOT NULL,
    corpus_version      SMALLINT NOT NULL,
    global_term_count   BIGINT NOT NULL,
    document_frequency  INTEGER NOT NULL,
    is_active           BOOLEAN NOT NULL DEFAULT TRUE,
    created_at          TIMESTAMPTZ NOT NULL DEFAULT NOW(),
    UNIQUE (token, corpus_version)
);
```

```sql
-- Sparse document-term matrix
CREATE TABLE lda_document_terms (
    article_id      TEXT,
    corpus_version  SMALLINT,
    term_id         INTEGER,
    term_count      INTEGER NOT NULL,
    PRIMARY KEY (article_id, corpus_version, term_id)
);
```

The loading process proceeds in three conceptual steps.

2.4.1 2.4.1 Building the per-article documents

For each article in the canonicalized corpus:

- All canonical tokens that belong to the **active vocabulary** are collected.
- Two simple counts are computed:
  - `token_count`: total number of tokens in the article, and
  - `unique_token_count`: number of distinct tokens in the article.

These values, together with the `article_id` and chosen `*corpus_version*` = 1, are inserted into `lda_documents`. At this point, each row in `lda_documents` represents the cleaned bag-of-words view of a single article under a specific corpus construction.

2.4.2 2.4.2 Constructing the vocabulary with frequencies

From our two previous counters, we already have:

- For each token in the **active vocabulary**:
  - `global_term_count`: the total number of times the token appears across all articles in this corpus version; and
  - `document_frequency`: the number of distinct articles containing at least one occurrence of the token.

These aggregates, with the cleaned and stemmed token symbol, are loaded into `lda_vocabulary` for the chosen `*corpus_version*` = 1. The `is_active` flag is set to `TRUE` (By default);

2.4.3 2.4.3 Populating the document–term matrix

Finally, we construct the sparse document–term matrix:

- For each article and each token in the active vocabulary that appears in that article, we compute the number of occurrences of that token.
- Each such pair is mapped to a vocabulary identifier via `term_id` and `article_id`.
- A row is inserted into `lda_document_terms` with `(article_id, corpus_version, term_id, term_count)`.

This table provides the integer counts consumed by LDA, while `lda_documents` and `lda_vocabulary` supply the corresponding textual and frequency metadata. Together, the three tables define a versioned, fully auditable corpus representation: changing the cleaning rules or vocabulary thresholds simply results in a new `corpus_version`, allowing multiple LDA runs to coexist without losing the provenance of earlier constructions.

[7]:
```python
from notebooks_utils.data_notebooks_utils.corpus_exploration_and_cleaning_utils.
↪corpus_exploration_and_cleaning_utils import (
    delete_parquet_chunks, summarize_and_filter_vocabulary
)

frequency_counters = summarize_and_filter_vocabulary(frequency_counters)
```

```
Top 20 tokens by global term count
------------------------------------------------------------
rank  token                   term_count     doc_freq
   1  __NUM__                   32279283       361553
   2  share                      4348482       314374
   3  stock                      3898699       300498
   4  compani                    3370516       332437
   5  quarter                    2560099       260541
   6  rate                       2530495       271780
   7  price                      1756400       277663
   8  report                     1658094       298857
   9  inc                        1341065       300960
  10  th                         1336017       215816
  11  market                     1279727       302194
  12  research                   1188209       241271
  13  averag                     1126558       266006
  14  hold                       1116109       259685
  15  analyst                    1104046       261676
  16  year                       1096635       282367
  17  buy                        1067811       257957
  18  valu                       1028881       241053
  19  last                       1009093       273585
  20  ratio                      1001497       225618

Vocabulary summary (min document frequency = 25)
------------------------------------------------------------
vocab_size_before             455080
vocab_size_after               37464
tokens_removed                417616
fraction_removed              0.9177
```

[12]:
```python
from notebooks_utils.data_notebooks_utils.corpus_exploration_and_cleaning_utils.
↪load_tables import load_corpus_tables
load_corpus_tables(frequency_counters, logger) # This is a No-OP if real_run is␣
↪not set to TRUE. Takes approximatly 50 minutes.
delete_parquet_chunks() # This is a No-OP if real_run is not set to TRUE.
```