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Every problem has a solution,
it may sometimes just need another
PERSPECTIVE.

PRESIDENTIAL COMMUNICATIONS OFFICE

GROUP 7'S HACKATHON OUTPUT

PROBLEM

How do different sources (MSM and SM) portray the Presidential Communications Office?

01

Which are the top 5 sources by number of stories?

02

Which country has the most positive sentiment stories?

03

What's the most common keyword/topic?

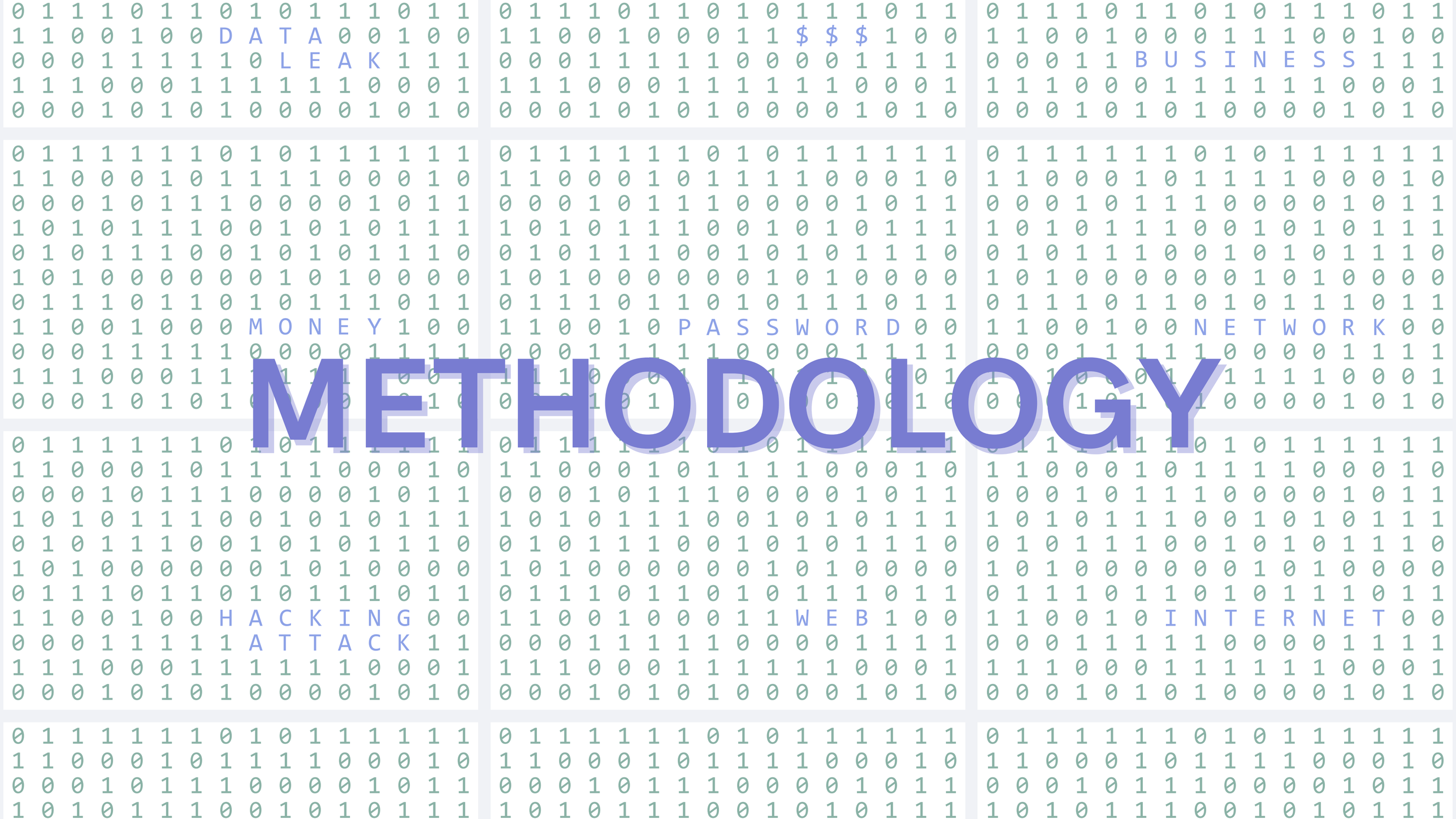
04

Which week had the most stories?

05

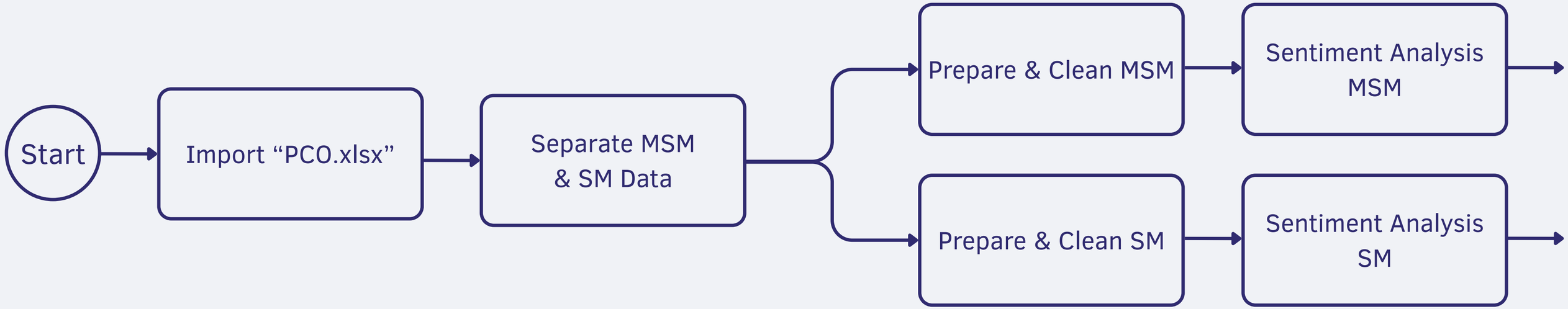
Which source has the highest average reach?

MSM vs SM


METHODOLOGY

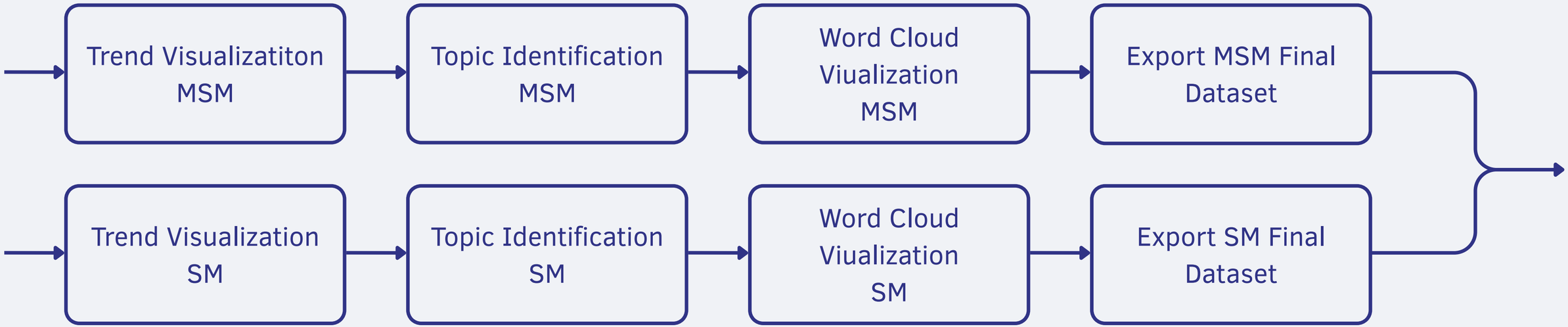
METHODOLOGY

Data Analysis Process



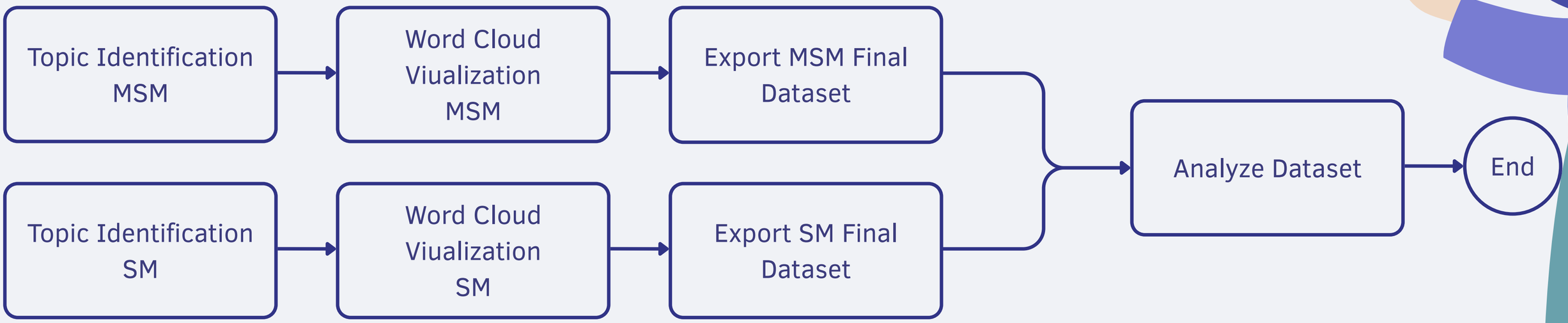
METHODOLOGY

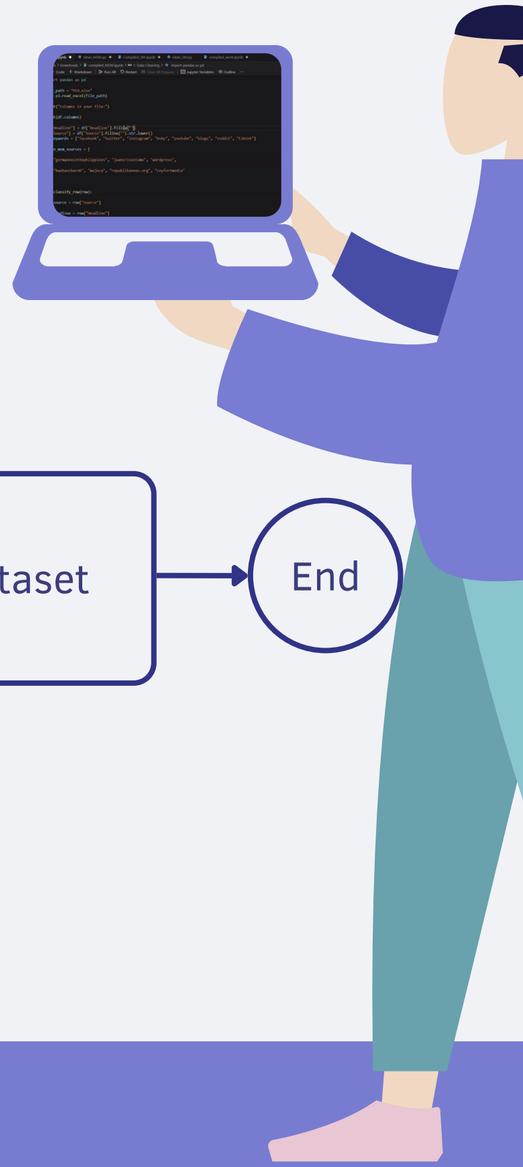
Data Analysis Process



METHODOLOGY

Data Analysis Process

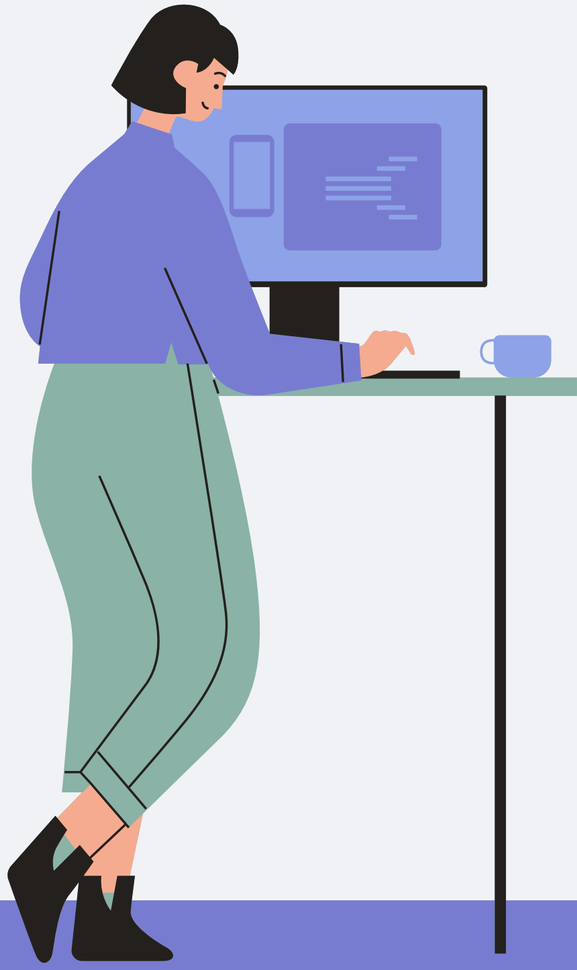




METHODOLOGY

Limitations

- Results depend on **data quality & completeness**
- **Sample bias** possible in source data
- **Rule-based cleaning** cannot resolve all anomalies
- **Library constraints** (performance & interpretability limits)
- Automated checks **may miss context-specific errors**

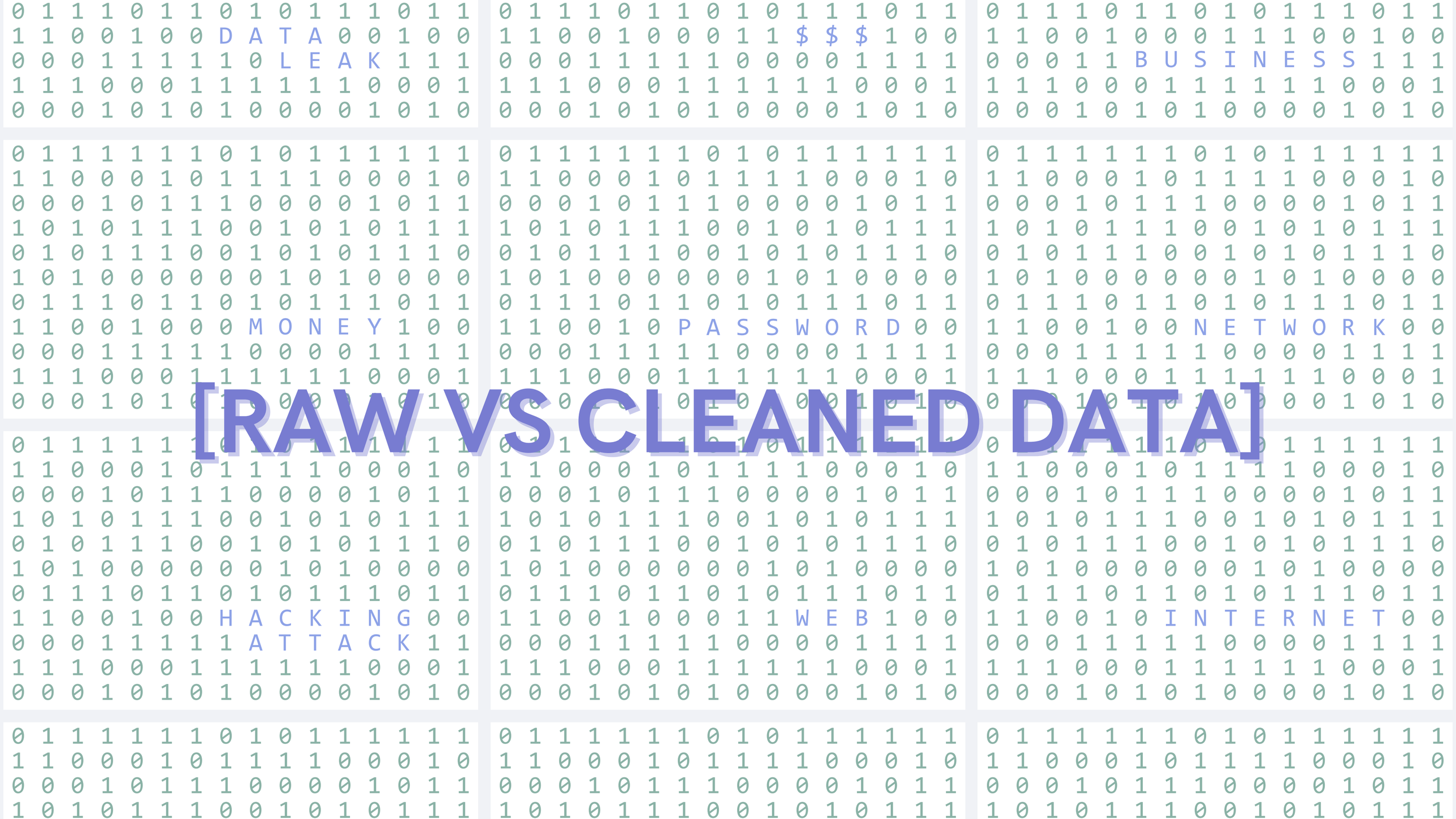


METHODOLOGY

Caveats

- Some records may remain **incomplete or duplicated**
- **Time sensitivity:** datasets are snapshots, not live updates
- **Textual ambiguity** in headlines/keywords affects sentiment scoring
- Scaling up may face **performance or memory constraints**


DATA


[RAW VS CLEANED DATA]

Raw Data

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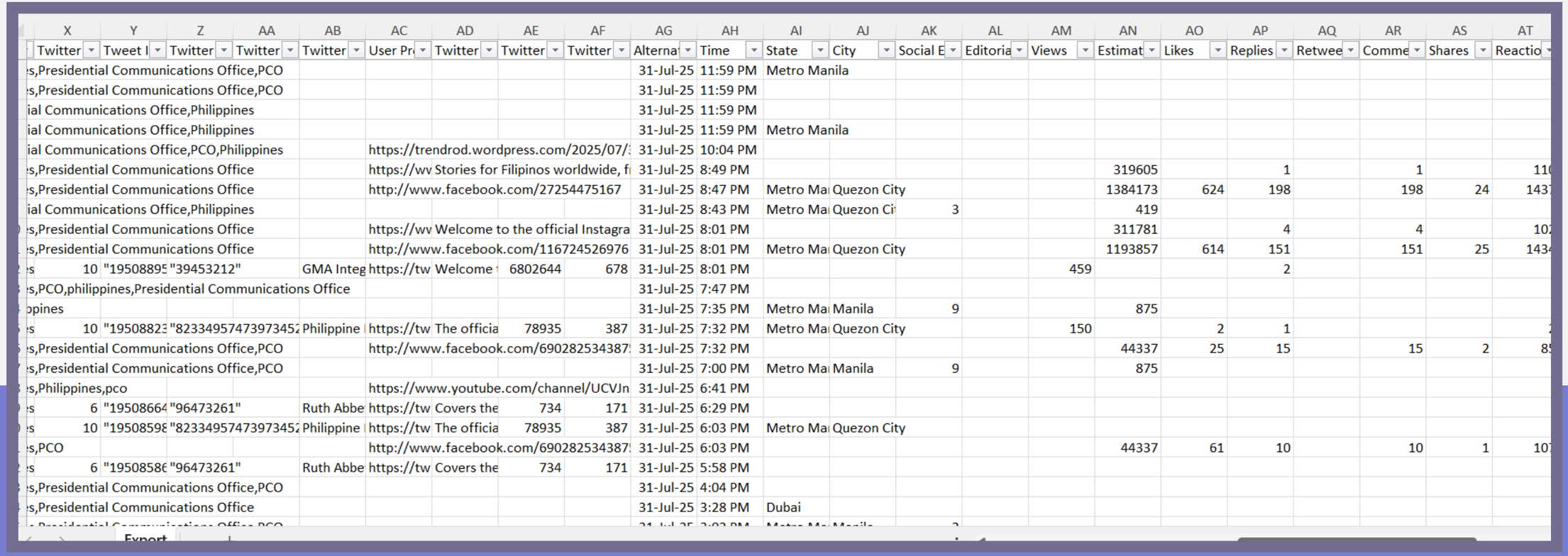

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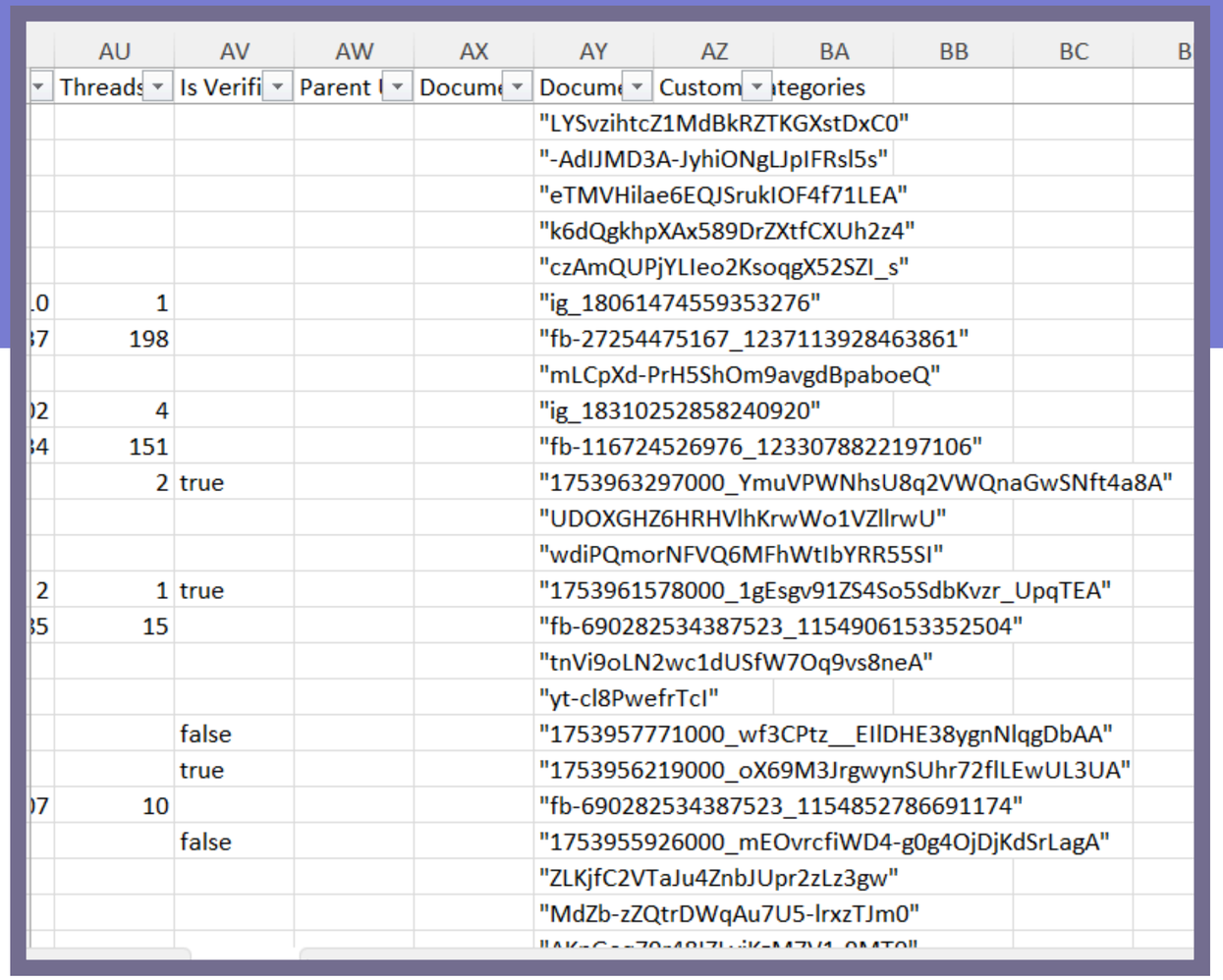
Export

Raw Data

Raw data



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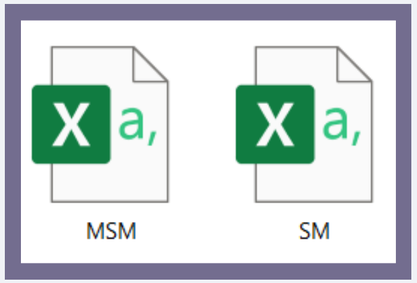

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Data Cleaning


DATA CLEANING
[SEPARATING THE DATA]

```python
import pandas as pd

file_path = "PCO.xlsx"
df = pd.read_excel(file_path)

print("Columns in your file:")

print(df.columns)
```

Importing necessary library and importing the file

```python
df["Headline"] = df["Headline"].fillna("")
df["Source"] = df["Source"].fillna("").str.lower()
sm_keywords = ["facebook", "twitter", "instagram", "bsky", "youtube", "blogs", "reddit", "tiktok"]

force_msm_sources = [

    "germanexinthephilppines", "juancrisostomo", "wordpress",

    "kwebanibarok", "majeca", "republikanews.org", "reyfortmedia"
```

Replacing the missing values Headline and Source column

```python
def classify_row(row):
    source = row["Source"]
    headline = row["Headline"]
    if any(keyword in source for keyword in force_msm_sources):
        return "MSM"
    if headline.strip() == "":
        return "SM"
    if any(keyword in source for keyword in sm_keywords):
        return "SM"
    return "MSM"
```

Conditional code to identify which data category is appropriate: SM or MSM

```python
df["Category"] = df.apply(classify_row, axis=1)

msm_df = df[df["Category"] == "MSM"]

sm_df = df[df["Category"] == "SM"]
```

Creating new column category name for MSM and SM

```
msm_df.to_csv("MSM.csv", index=False, encoding="utf-8-sig")

sm_df.to_csv("SM.csv", index=False, encoding="utf-8-sig")
```

Exporting the two separated files into SM and MSM CSV files


DATA CLEANING
[MSM]

```python
import pandas as pd
import re
import string

file_path = "MSM.csv"
df = pd.read_csv(file_path)
```

Importing necessary libraries and importing the MSM CSV file

```
df_clean = df.drop_duplicates(subset=["Source Link"], keep="first")
df_clean = df_clean.dropna(subset=["Date", "Headline", "Source", "Country"])
```

Dropping the null values or missing values

```python
def parse_date(row):
    date_str = row["Date"] if pd.notnull(row["Date"]) else row.get("Alternate Date Format", None)
    try:
        parsed = pd.to_datetime(date_str, errors="coerce")
        return parsed.date() if pd.notnull(parsed) else pd.NaT
    except:
        return pd.NaT

df_clean.loc[:, "Clean Date"] = df_clean.apply(parse_date, axis=1)
df_clean = df_clean.dropna(subset=["Clean Date"])
df_clean.loc[:, "Clean Date"] = pd.to_datetime(df_clean["Clean Date"]).dt.strftime("%m-%d-%Y")
```

Standardization of date format

```
def normalize_source(source):
    s = str(source).strip().lower()

    s = re.sub(r"www\.", "", s)
    s = re.sub(r"\.com|\.ph|\.net|\.org", "", s)
    s = re.sub(r"\s+", " ", s)

    words = s.split()
    result_words = []
    for w in words:
        if w == "abs":
            result_words.append("ABS")
        elif w == "cbn":
            result_words.append("CBN")
        elif w == "msn":
            result_words.append("MSN")
        elif w == "ptv":
            result_words.append("PTV")
        else:
            result_words.append(w.title())
    return " ".join(result_words)
df_clean.loc[:, "Source"] = df_clean["Source"].apply(normalize_source)
```

Removing prefixes, normalizing the source column, capitalizing the acronyms

```python
def normalize_headline(text):
    if pd.isnull(text):
        return ""
    text = text.lower()
    text = re.sub(f"[{re.escape(string.punctuation)}]", "", text)
    text = re.sub(r"\s+", " ", text).strip()
    return text
```

Normalizing the headlines, removing punctuation, trimming spaces

```
df_clean["headline_key"] = df_clean["Headline"].apply(normalize_headline)
df_clean = df_clean.drop_duplicates(subset=["headline_key"], keep="first")
df_clean = df_clean.drop(columns=["headline_key"])
```

Removing duplicate headlines

```python
for col in ["Opening Text", "Influencer", "Key Phrases"]:
    if col in df_clean.columns:
        df_clean[col] = df_clean[col].fillna("Unknown")
        df_clean[col] = df_clean[col].replace(r"^\s*$", "Unknown", regex=True)
```

Replacing the empty cells with "Unknown"

```
social_echo_cols = ["Twitter Social Echo", "Facebook Social Echo", "Reddit Social Echo"]
for col in social_echo_cols:
    if col in df_clean.columns:
        df_clean[col] = pd.to_numeric(df_clean[col], errors="coerce").fillna(0).astype(int)
```

Data imputation, converting social echo as integer, replacing empty cells with 0 for numerical columns

```python
if all(col in df_clean.columns for col in social_echo_cols):
    df_clean["Social Echo Total"] = (
        df_clean["Twitter Social Echo"]
        + df_clean["Facebook Social Echo"]
        + df_clean["Reddit Social Echo"]
    ).astype(int)
elif "Social Echo Total" in df_clean.columns:
    df_clean["Social Echo Total"] = pd.to_numeric(df_clean["Social Echo Total"], errors="coerce").fillna(0).astype(int)
```

Recalculating the social echo by summing the 3 columns

```
df_clean = df_clean[~df_clean["Headline"].str.contains("content from this publisher", case=False, na=False)]
df_clean = df_clean[~df_clean["Source Link"].str.contains("proquest", case=False, na=False)]
df_clean = df_clean[~df_clean["Headline"].str.contains("test", case=False, na=False)]
df_clean = df_clean[df_clean["Source Link"].str.strip() != ""]
```

Removing these hit keywords from headline, source link, and headline

```
if "Hit Sentence" in df_clean.columns:
    df_clean = df_clean[~df_clean["Hit Sentence"].str.contains(r"\[Courtesy:|\[Photo courtesy\]", case=False, na=False)]
```

Removing this keyword from hit sentence column

```
df_clean = df_clean.drop(columns=[c for c in cols_to_drop if c in df_clean.columns])

if "Country" in df_clean.columns:
    df_clean["Country"] = df_clean["Country"].astype(str).str.strip().str.title()

if "Headline" in df_clean.columns:
    df_clean["Headline"] = df_clean["Headline"].astype(str).str.strip()
    df_clean["Headline"] = df_clean["Headline"].replace(r"\s+", " ", regex=True)
    df_clean["Headline"] = df_clean["Headline"].str.title()

text_cols = ["Opening Text", "Hit Sentence"]
for col in text_cols:
    if col in df_clean.columns:
        df_clean[col] = df_clean[col].astype(str).str.strip()
        df_clean[col] = df_clean[col].replace(r"\s+", " ", regex=True)
        df_clean[col] = df_clean[col].str.capitalize()
```

Normalizing the headline, country, opening text, and hit sentence column (Capitalizing)

```python
if "Clean Date" in df_clean.columns:
    cols = ["Clean Date"] + [c for c in df_clean.columns if c != "Clean Date"]
    df_clean = df_clean[cols]
```

Moving the new cleaned date to the first column

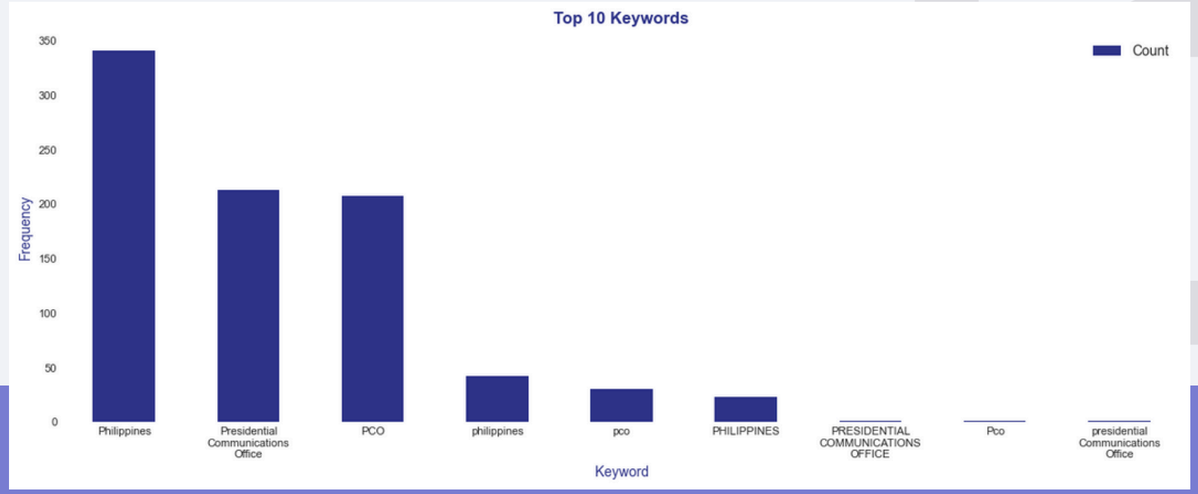
```
if "Keywords" in df_clean.columns:
    df_clean["Keywords"] = df_clean["Keywords"].apply(standardize_keyphrases)
```

Standardization of Keywords Column

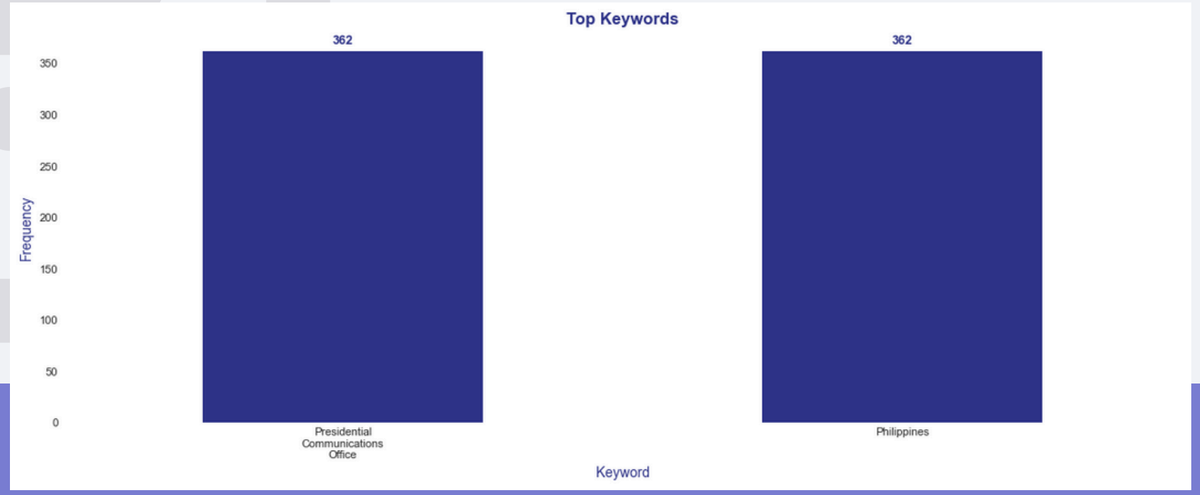
```python
def standardize_keyphrases(text):
    if pd.isna(text) or str(text).strip() == "":
        return "Unknown"
    text = str(text)
    parts = re.split(r'[;,|/•]+', text)
    normalized = []
    for p in parts:
        p = p.strip()
        if p == "":
            continue
        low = p.lower()
        if "pco" in low or "presidential communications" in low:
            normalized.append("Presidential Communications Office")
        elif "philippines" in low or "pilipinas" in low or "pilipino" in low:
            normalized.append("Philippines")
        else:
            normalized.append(p.title())
    seen = set()
    final_list = []
    for item in normalized:
        if item not in seen:
            final_list.append(item)
            seen.add(item)
    return ", ".join(final_list) if final_list else "Unknown"

if "Key Phrases" in df_clean.columns:
    df_clean["Key Phrases"] = df_clean["Key Phrases"].apply(standardize_keyphrases)
```

Standardization of Key Phrases Column

Before



After



Result of standardization of key phrases and keywords column

```python
def detect_language_for_country(text):
    if pd.isna(text) or str(text).strip() == "":
        return None
    try:
        return detect(text)
    except LangDetectException:
        return None

def map_language_to_country(lang_code):
    mapping = {
        "tl": "Philippines",
        "fil": "Philippines",
        "en": "United States",
        "ja": "Japan",
        "ko": "South Korea",
        "zh": "China",
        "fr": "France",
        "es": "Spain",
        "de": "Germany",
        "ms": "Malaysia",
        "id": "Indonesia",
    }
    return mapping.get(lang_code, None)
```

Fill missing Country based on Hit Sentence language

```python
if "Country" in df_clean.columns and "Hit Sentence" in df_clean.columns:
    def fill_country(row):
        country = str(row["Country"]).strip().lower()
        if country == "" or country == "unknown" or country == "nan":
            lang_code = detect_language_for_country(row["Hit Sentence"])
            inferred_country = map_language_to_country(lang_code)
            return inferred_country if inferred_country else "Unknown"
        return row["Country"]

    df_clean["Country"] = df_clean.apply(fill_country, axis=1)
```

Fill missing Country based on Hit Sentence language

```python
def detect_tl_or_en(text):
    if pd.isna(text) or str(text).strip() == "":
        return "English"
    try:
        lang_code = detect(str(text))
    except LangDetectException:
        return "English"

    if lang_code in ["tl", "fil"]:
        return "Tagalog"
    else:
        return "English"

if "Language" in df_clean.columns and "Hit Sentence" in df_clean.columns:
    def fill_language(row):
        lang = str(row["Language"]).strip().lower()
        if lang == "" or lang == "unknown" or lang == "nan":
            return detect_tl_or_en(row["Hit Sentence"])
        return row["Language"]

    df_clean["Language"] = df_clean.apply(fill_language, axis=1)
```

Detect Language based on Hit Sentence - Tagalog or English only

```
cols_to_drop = [
    "Subregion", "Desktop Reach", "Mobile Reach",
    "National Viewership", "Engagement", "AVE", "Twitter Authority",
    "Tweet Id", "Twitter Id", "Twitter Client", "Twitter Screen Name",
    "User Profile Url", "Twitter Bio", "Twitter Followers", "Twitter Following",
    "Alternate Date Format", "Time", "State", "City", "Editorial Echo",
    "Views", "Estimated Views", "Likes", "Replies", "Retweets",
    "Comments", "Shares", "Reactions", "Threads", "Is Verified",
    "Parent URL", "Document Tags", "Document ID", "Custom Categories"
]
```

Dropping the irrelevant columns

```
output_path = "MSM_cleaned.xlsx"
df_clean.to_excel(output_path, index=False, engine="openpyxl")
```

Exporting the new cleaned MSM file


DATA CLEANING
[SM]

```
df_clean = df.drop_duplicates(subset=["Source Link"], keep="first")

df_clean = df_clean.dropna(subset=["Date", "Source", "Country"])
def fill_headline(row):
```

Remove duplicates from the source link and delete rows with missing values in date, source, or country

```
    if pd.isna(row["Headline"]) or str(row["Headline"]).strip() == "":
        if pd.notna(row.get("Opening Text")) and str(row.get("Opening Text")).strip() != "":
            return row["Opening Text"].strip()
    return row["Headline"]

df_clean["Headline"] = df_clean.apply(fill_headline, axis=1)
```

Fill the missing cells in the headline column with the opening text value to prevent Python from dropping Twitter data

```
def normalize_source(source):

    s = str(source).strip().lower()

    s = re.sub(r"www\.", "", s)
    s = re.sub(r"\.com|\.ph|\.net|\.org", "", s)
    s = re.sub(r"\s+", " ", s)
    if "reddit" in s:

        return "Forums"

    return s.title()

df_clean.loc[:, "Source"] = df_clean["Source"].apply(normalize_source)
```

Replacing the Reddit source name as Forums

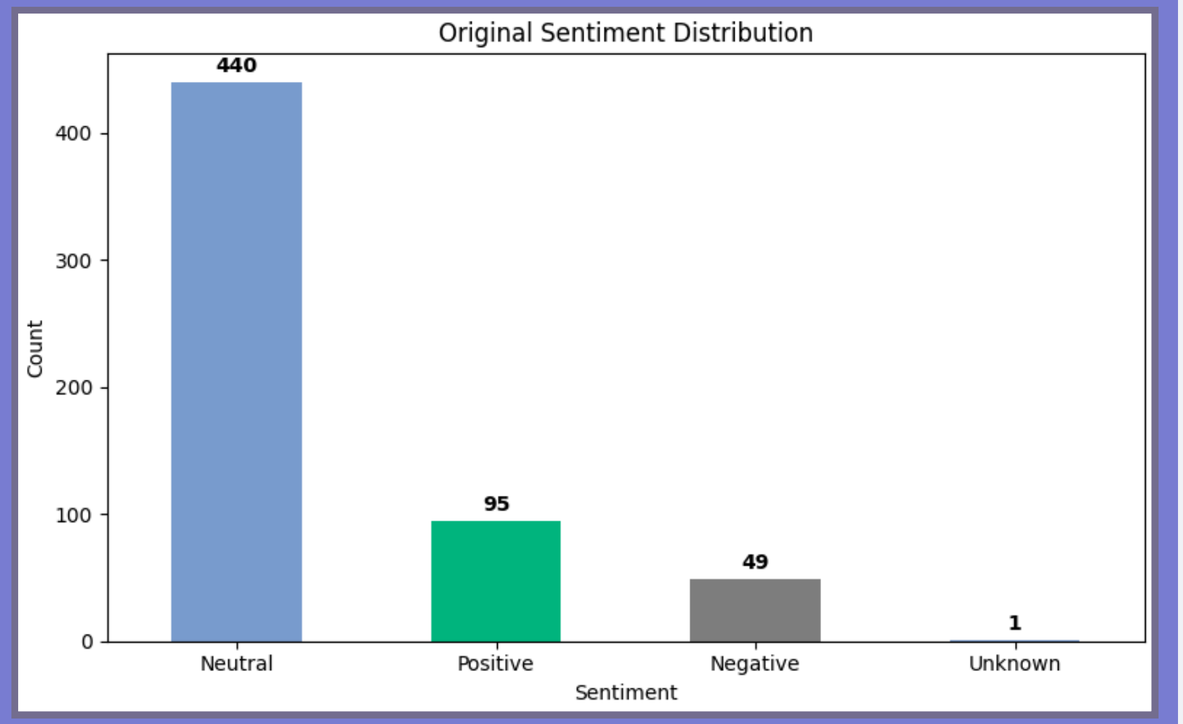
```python
def normalize_headline(text):

    if pd.isnull(text):

        return ""

    text = text.lower()

    text = re.sub(f"[{re.escape(string.punctuation)}]", "", text)

    text = re.sub(r"\s+", " ", text).strip()

    return text

df_clean["headline_key"] = df_clean["Headline"].apply(normalize_headline)

df_clean = df_clean.drop_duplicates(subset=["headline_key"], keep="first")

df_clean = df_clean.drop(columns=["headline_key"])
```

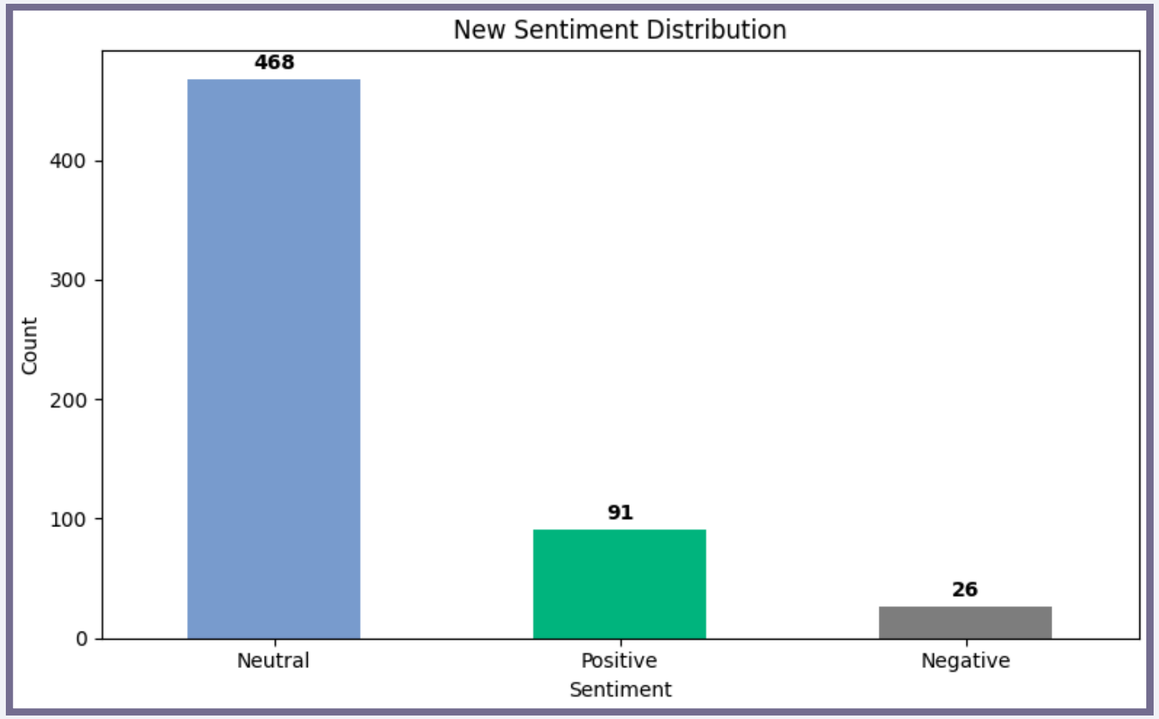
Standardise the headline column by removing punctuation, trimming spaces, and eliminating duplicate entries


MSM RESULTS

Sentiment Analysis

Original Sentiment vs New Sentiment



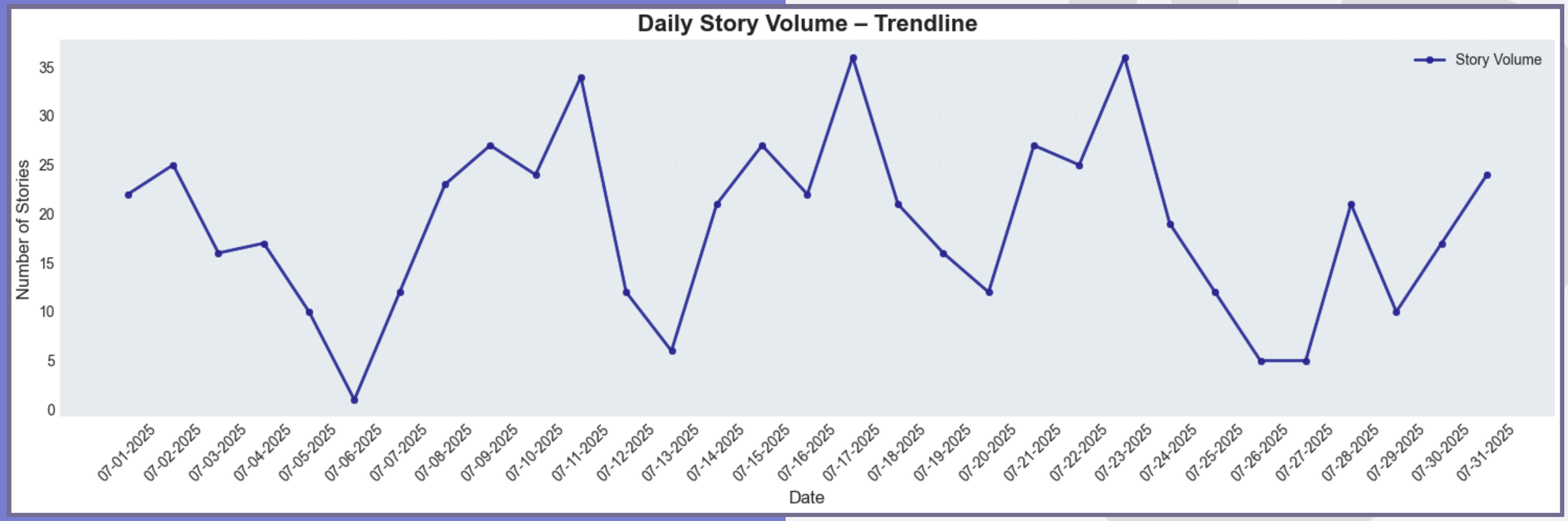


Sentiment Analysis

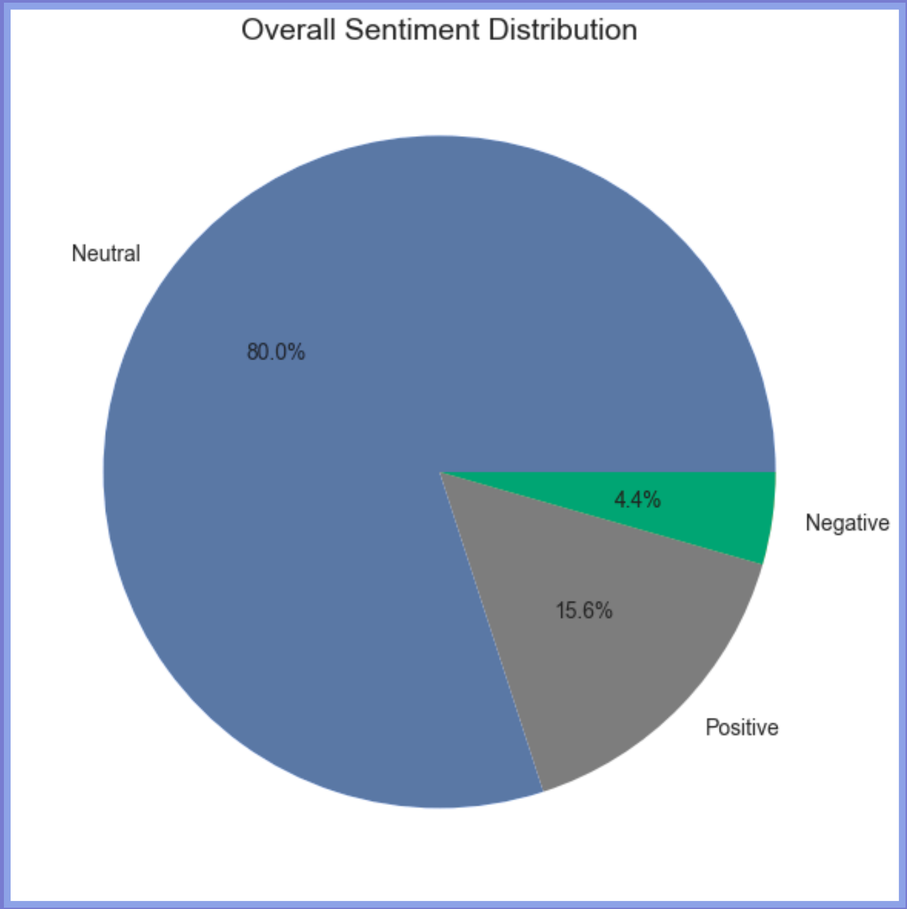
Sample Differences

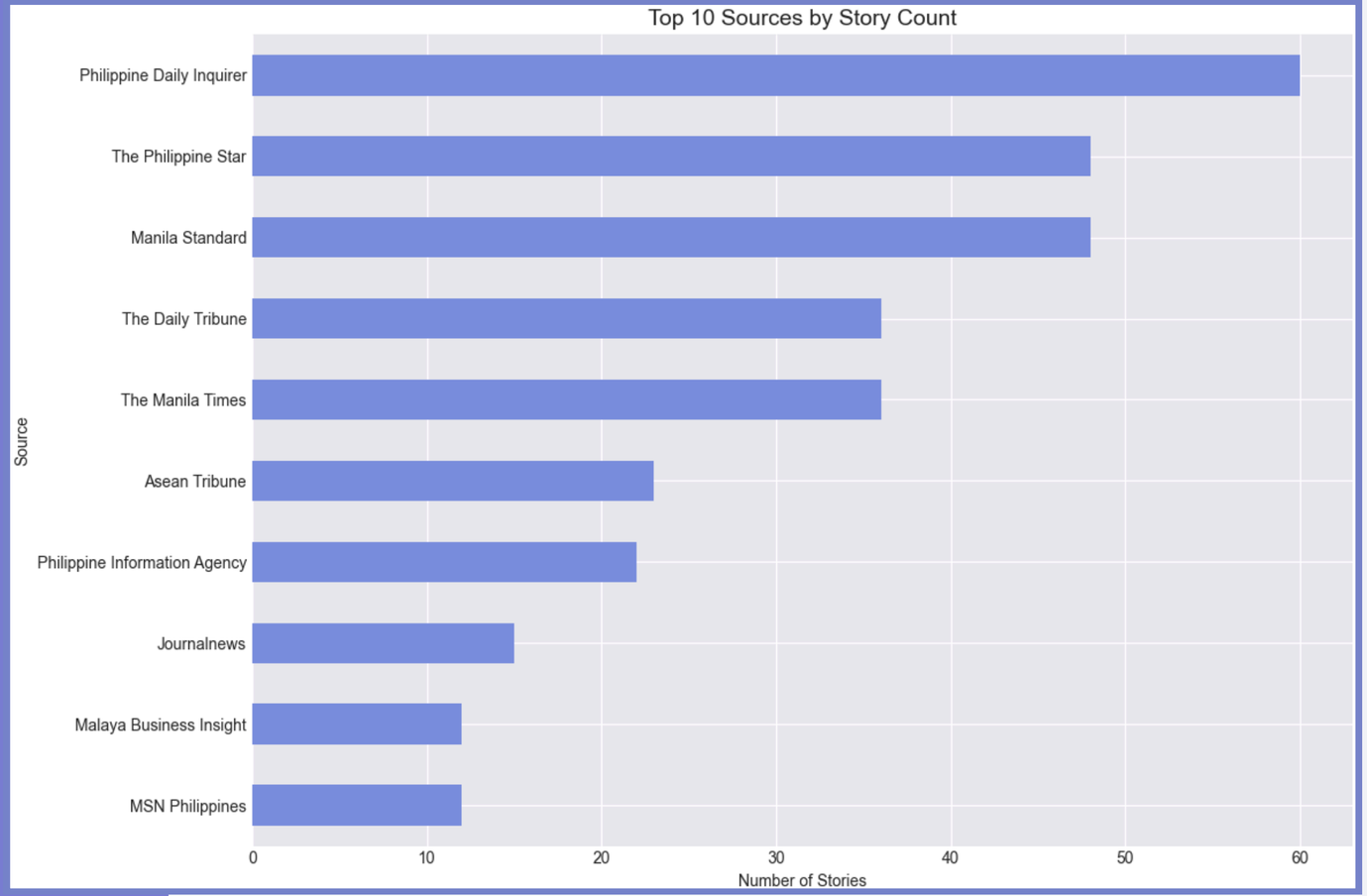
```
🧪 Showing 5 examples where the sentiment changed:

Headline: Paglabag Sa Protocol Sa Presidential Coverage, ‘Di Dapat Maulit - Ruiz
Original Sentiment: Negative
New Sentiment: Neutral
------------------------------------------------------------
Headline: Here'S The Full Text Of President Bongbong Marcos' Fourth State Of The Nation Address
Original Sentiment: Neutral
New Sentiment: Positive
------------------------------------------------------------
Headline: Philippines’ Marcos To Meet Trump Hoping To Secure Trade Deal
Original Sentiment: Neutral
New Sentiment: Positive
------------------------------------------------------------
Headline: Discount Express (From July 16): 50% Off On Manila Trains For Seniors, People Of Determination
Original Sentiment: Positive
New Sentiment: Neutral
------------------------------------------------------------
Headline: Gov’T Extends National Fiber Backbone Project To More Regions
Original Sentiment: Neutral
New Sentiment: Positive
------------------------------------------------------------
```

Trend Visualization

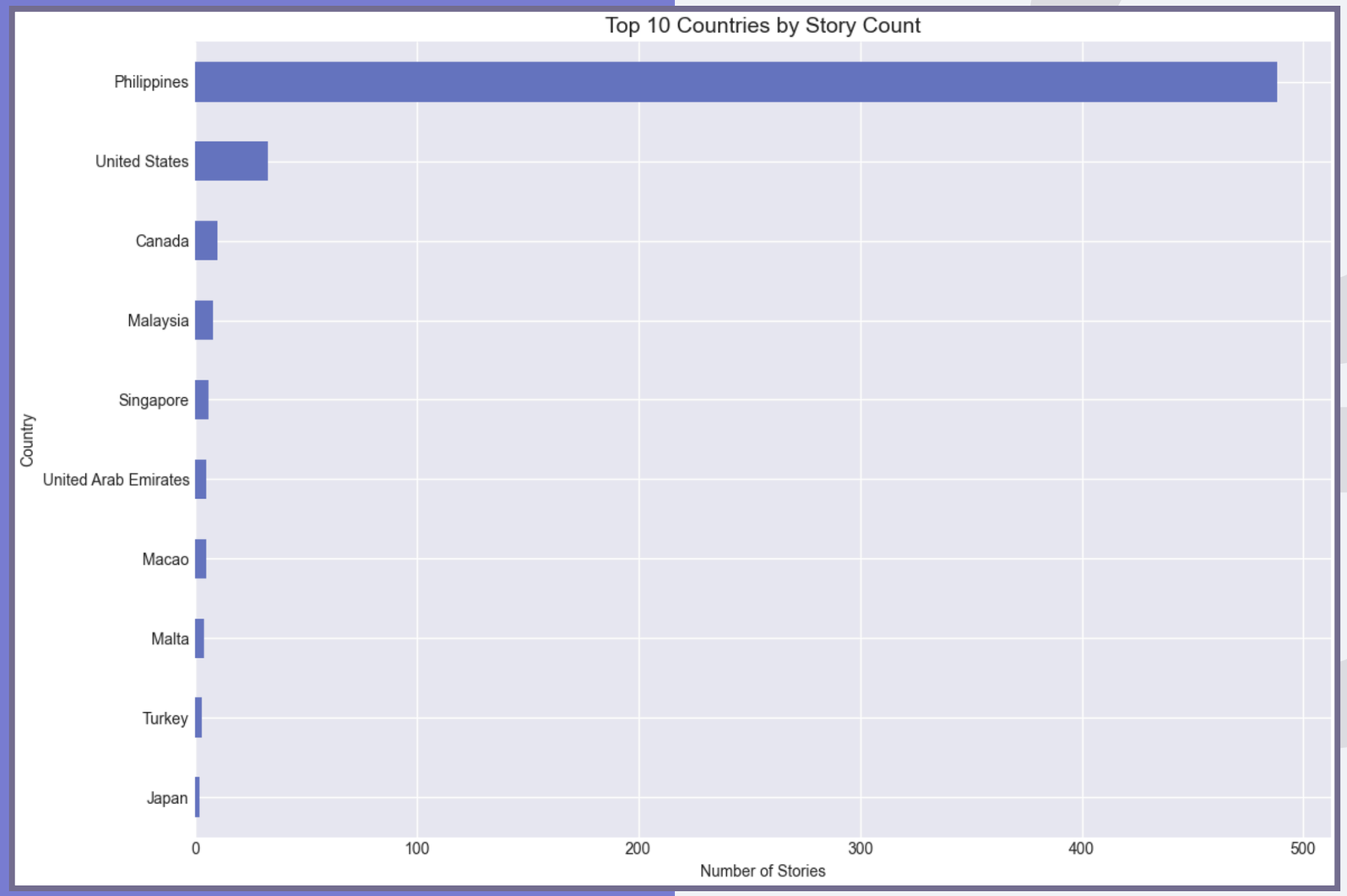


Trend Visualization

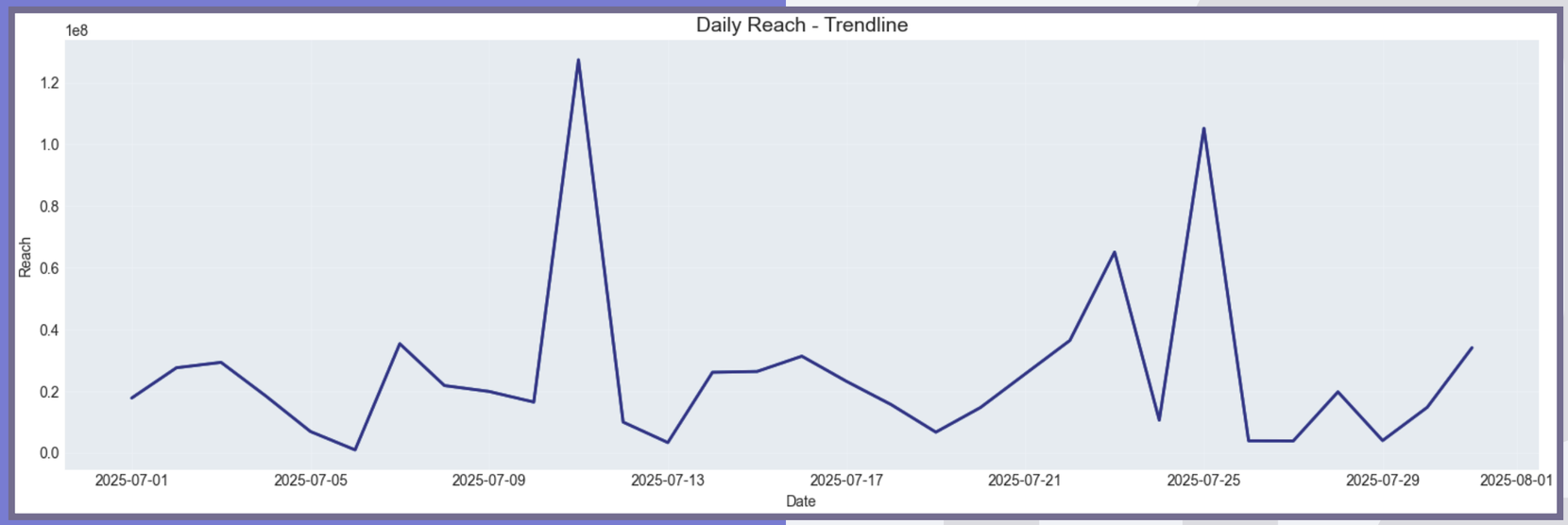


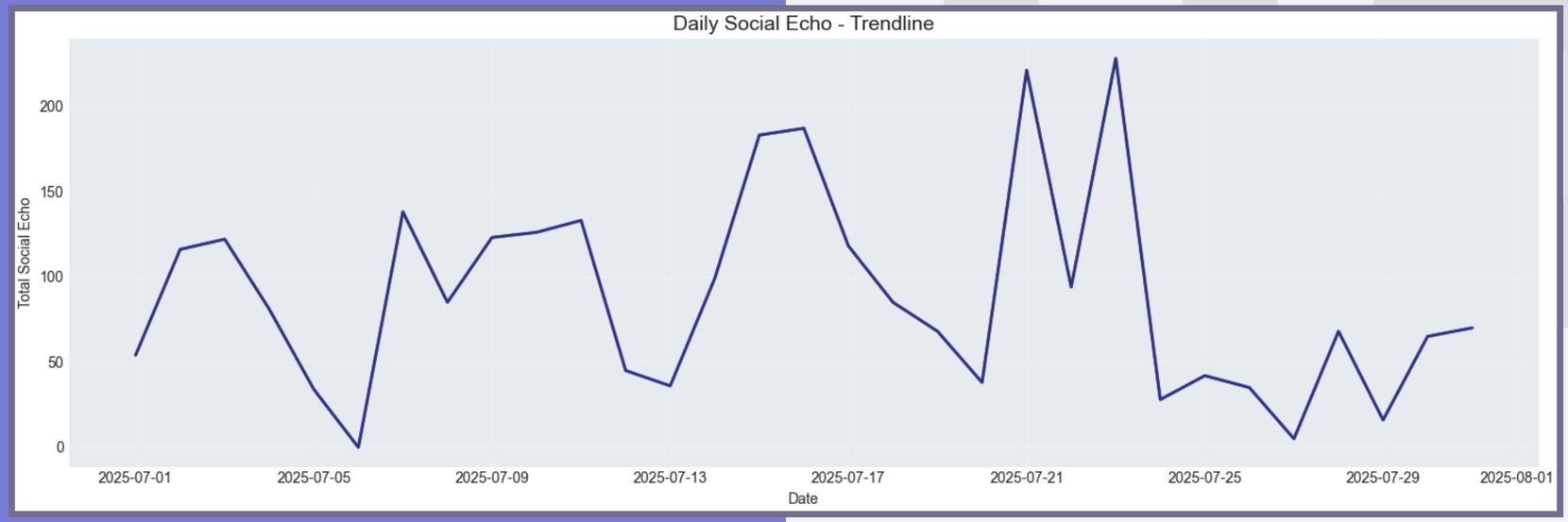


Trend Visualization



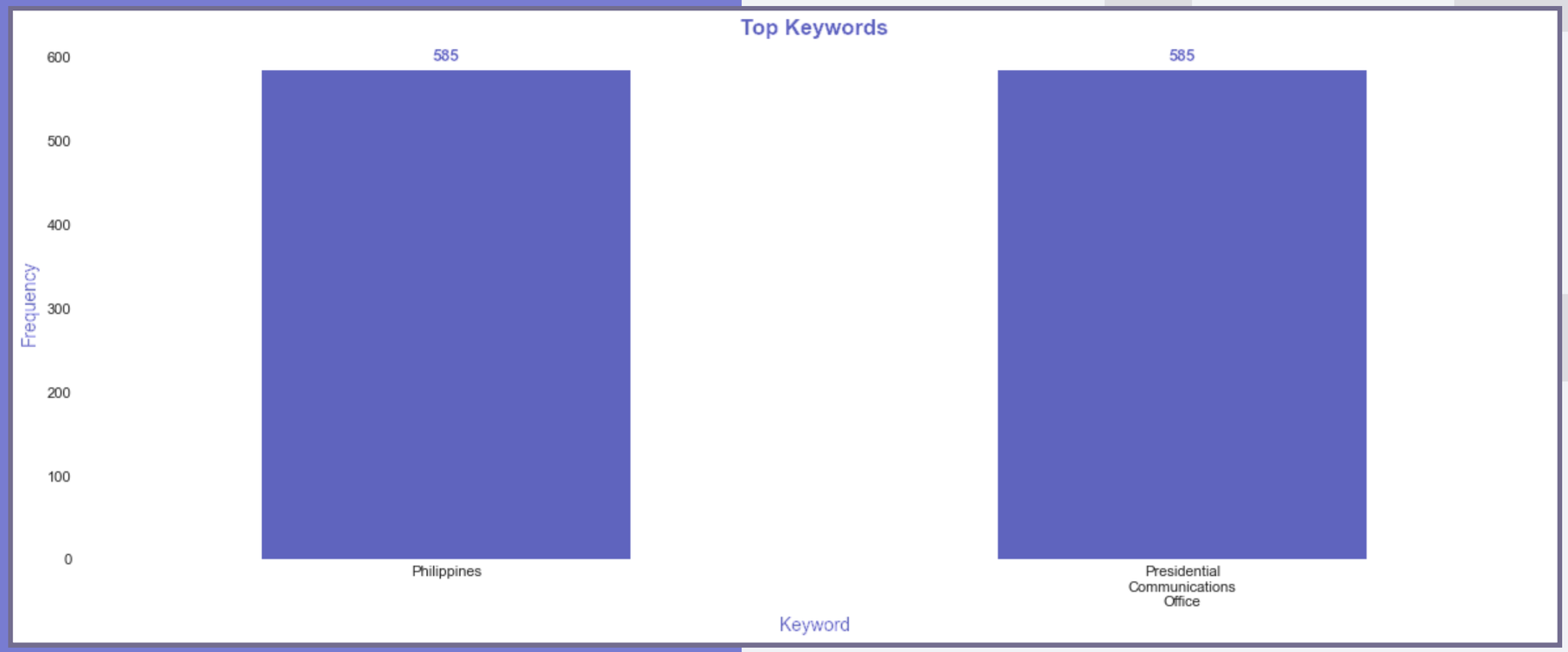
Trend Visualization





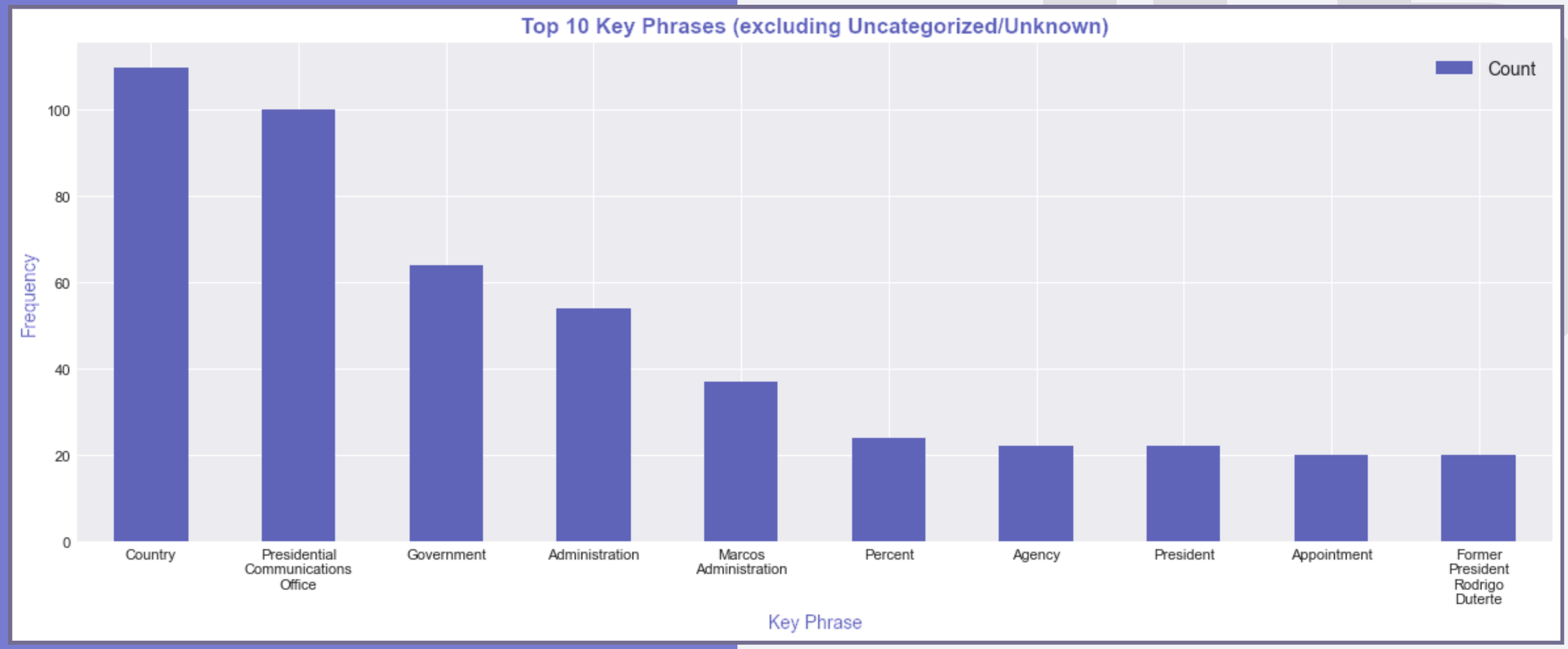
Topic Identification

Content Analysis - Top Common Keywords



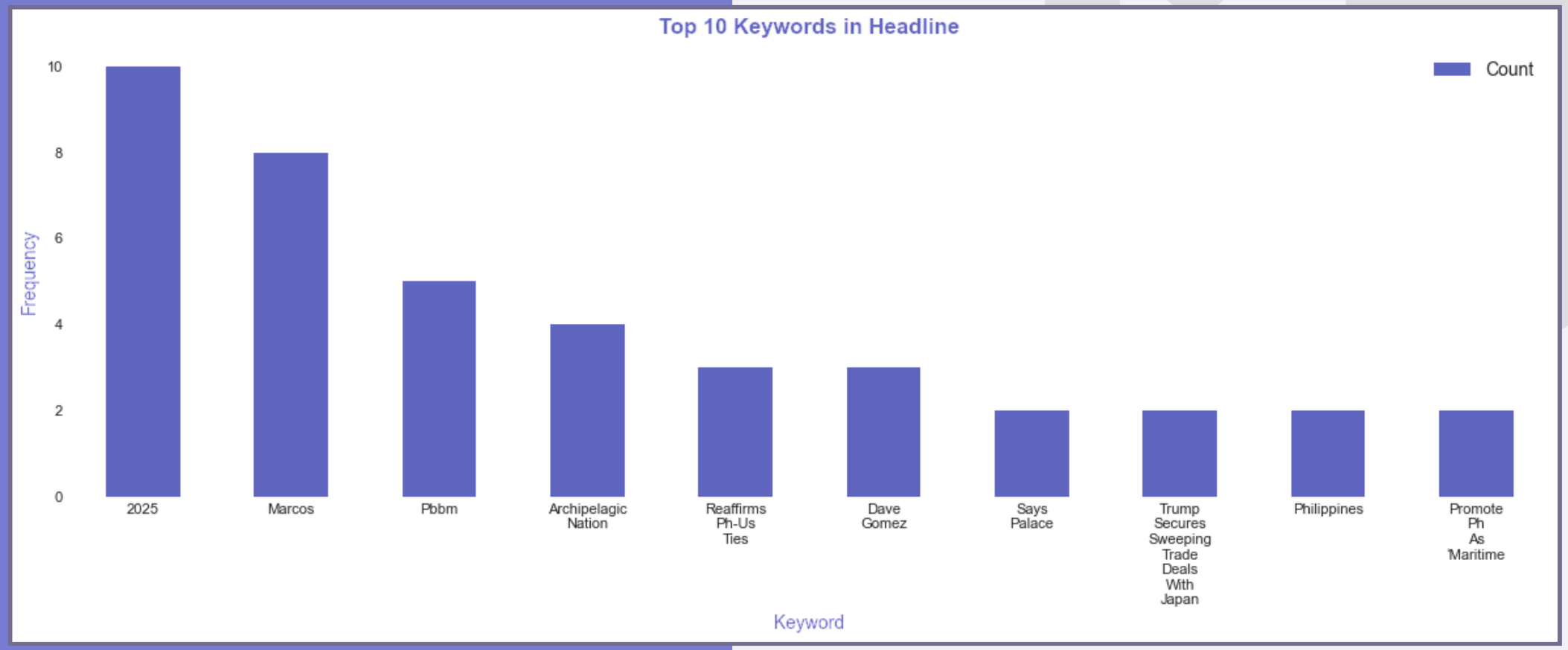
Topic Identification

Content Analysis - Top 10 Key Phrases



Topic Identification

Content Analysis - Top 10 Keywords in Headline



Word Cloud Visualization

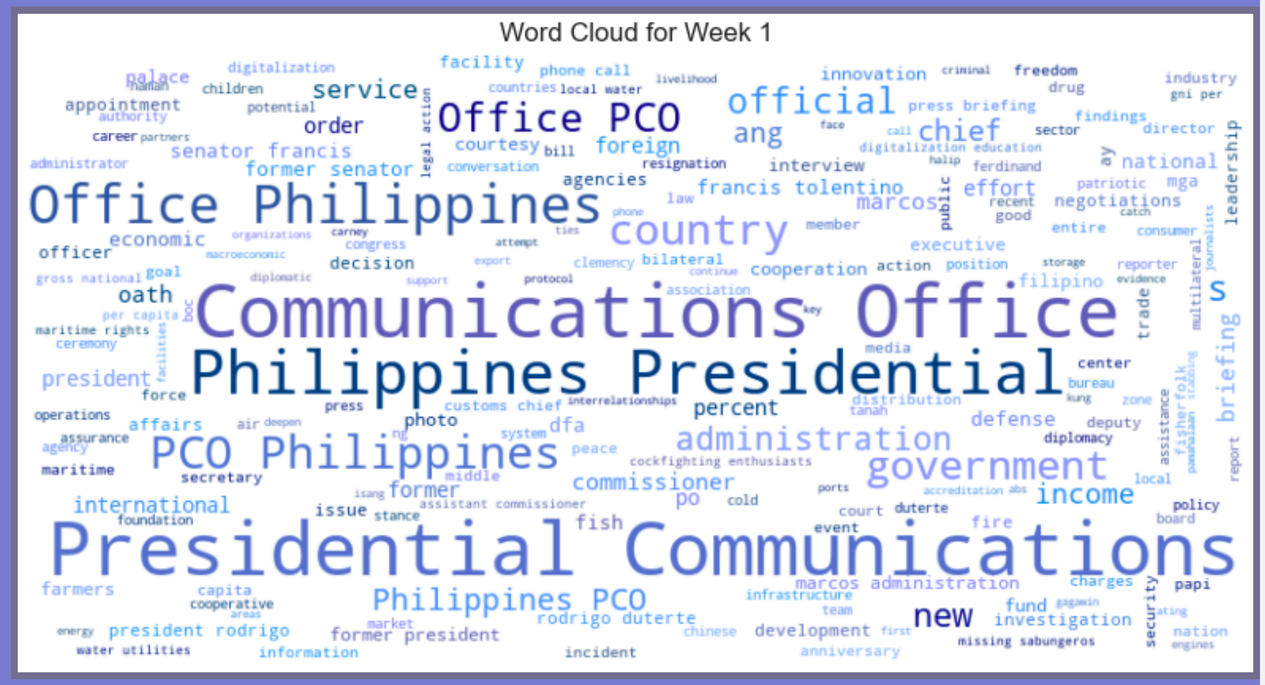
Visual Analysis - All Keywords and Phrases

Word Cloud Visualization

Visual Analysis - All Sentiment Categories

Word Cloud Visualization

Visual Analysis - Week 1 vs Week 2



Word Cloud Visualization

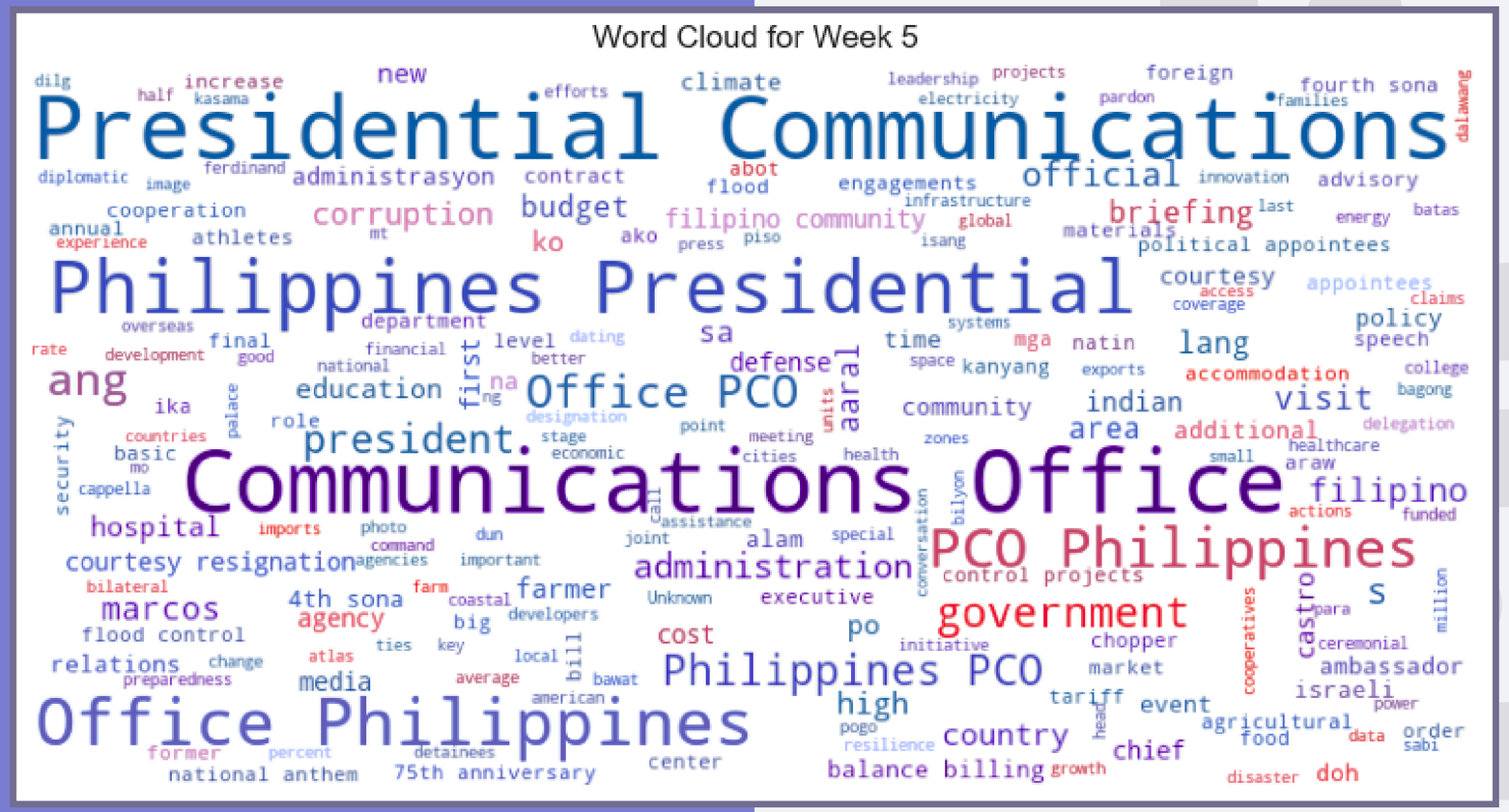
Visual Analysis - Week 3 vs Week 4

Week 3

Week 4

Word Cloud Visualization

Visual Analysis - Week 5



Week 5

Findings

Which are the top 5 sources by number of stories?

Source	Volume
1. Philippine Daily Inquirer	60
2. Manila Standard 2. The Philippine Star	48
3. The Daily Tribune 3. The Manila Times	36
4. Asean Tribune	23
5. Philippine Information Agency	22

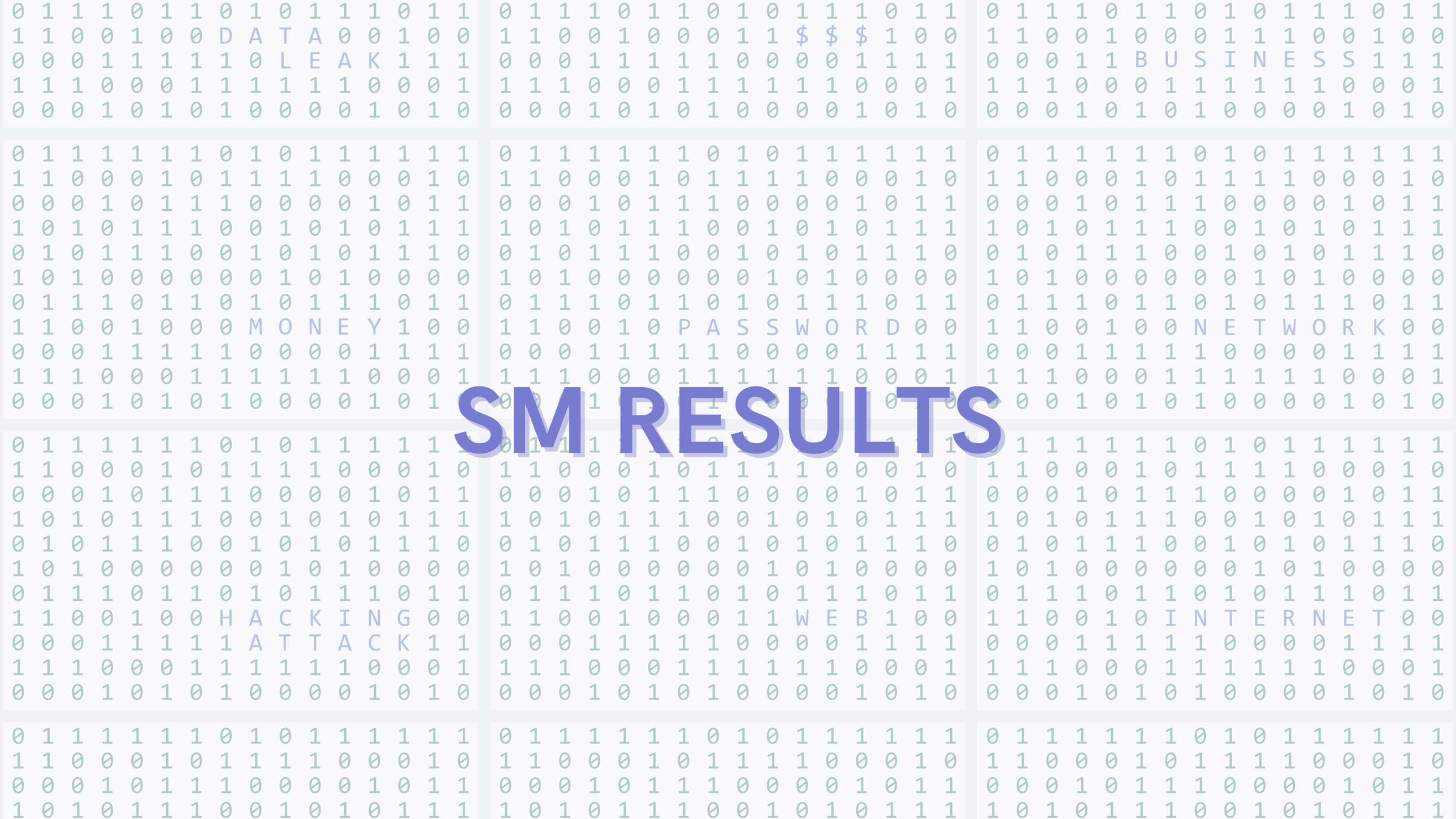
Findings

Which country has the most positive sentiment stories?

Country	Volume
1. Philippines	77
2. United States	4
3. Singapore	3
4. Malaysia	2

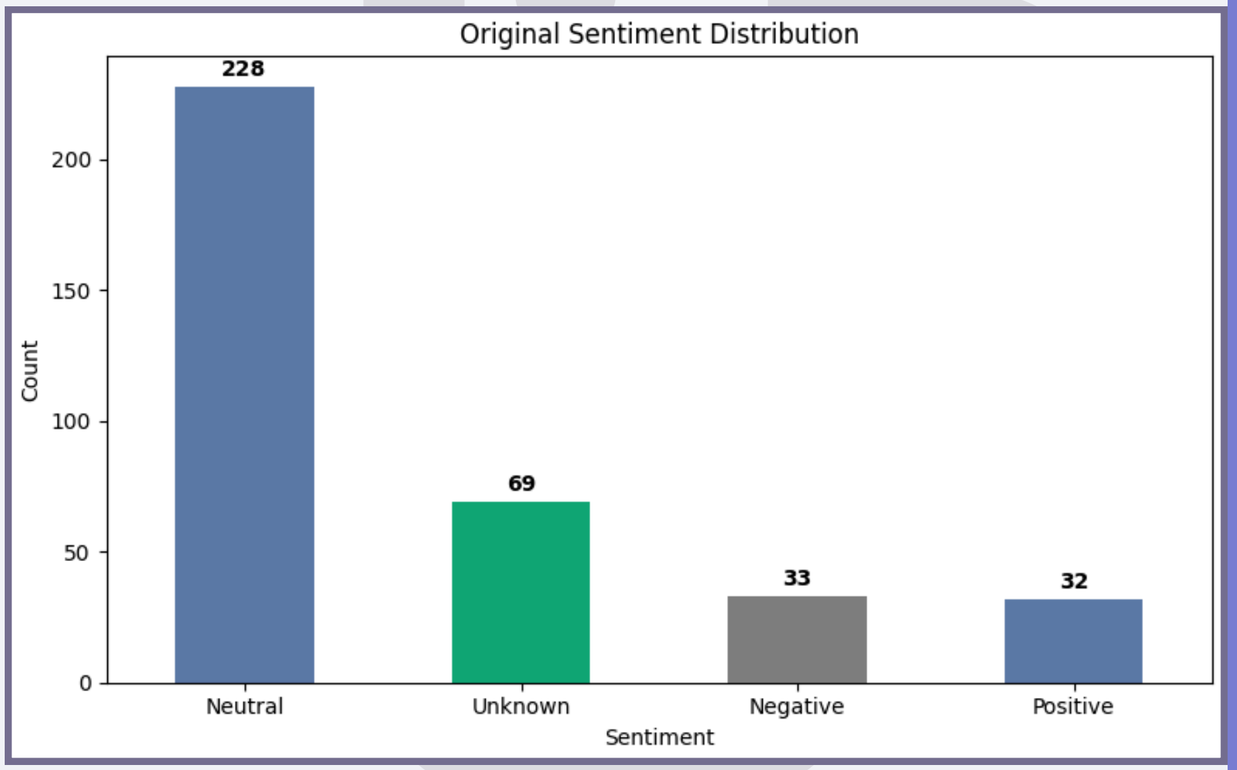
Findings

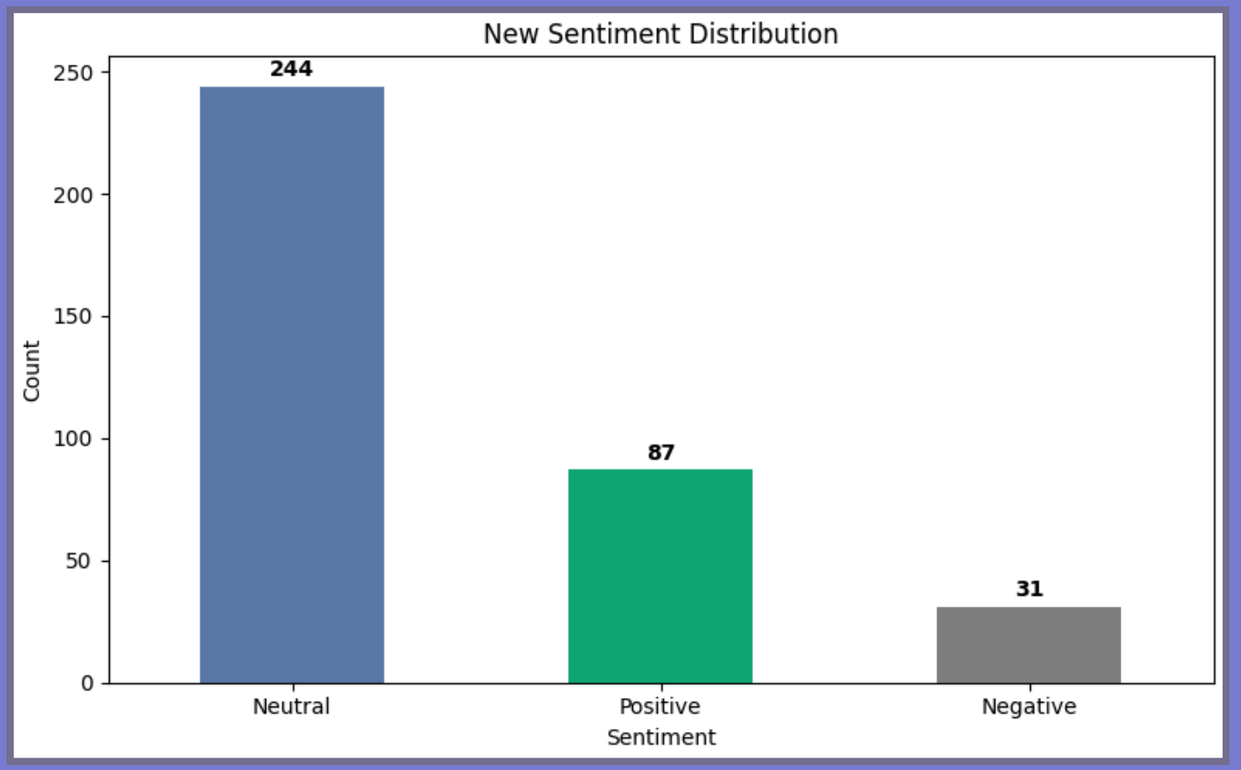
What's the most common keyword/topic?	Volume
Philippines, Presidential Communications Office	585
Which source has the highest average reach?	**Reach**
MSN	101,199,920


SM RESULTS

Sentiment Analysis

Original Sentiment vs New Sentiment



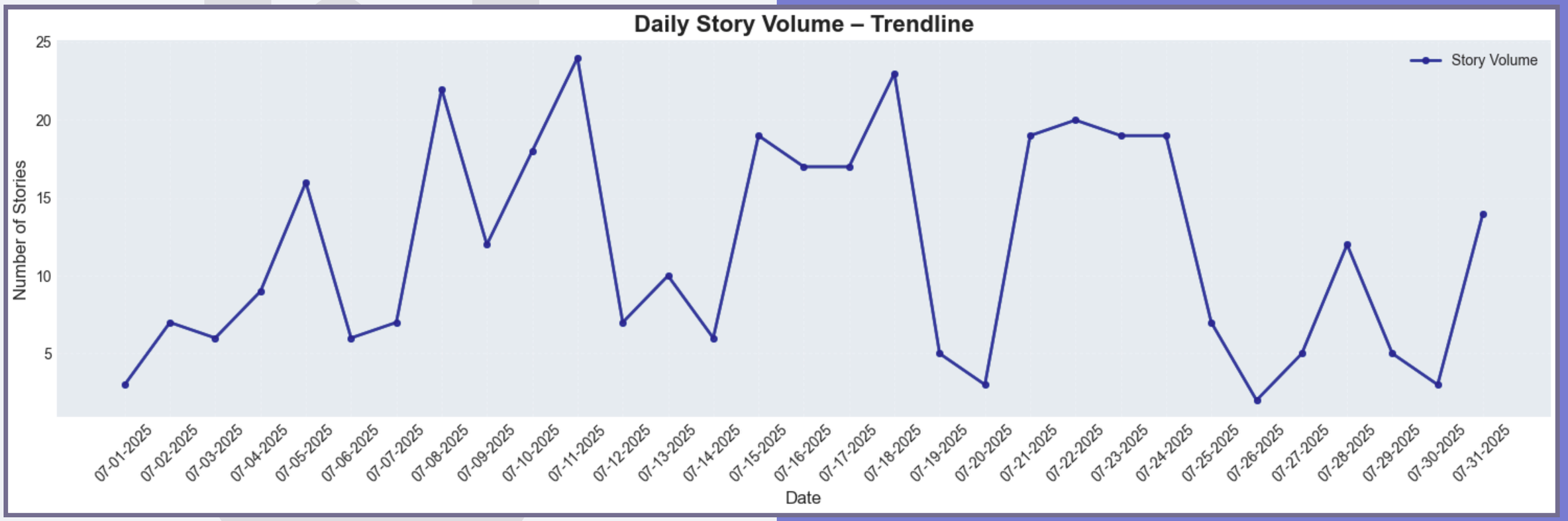


Sentiment Analysis

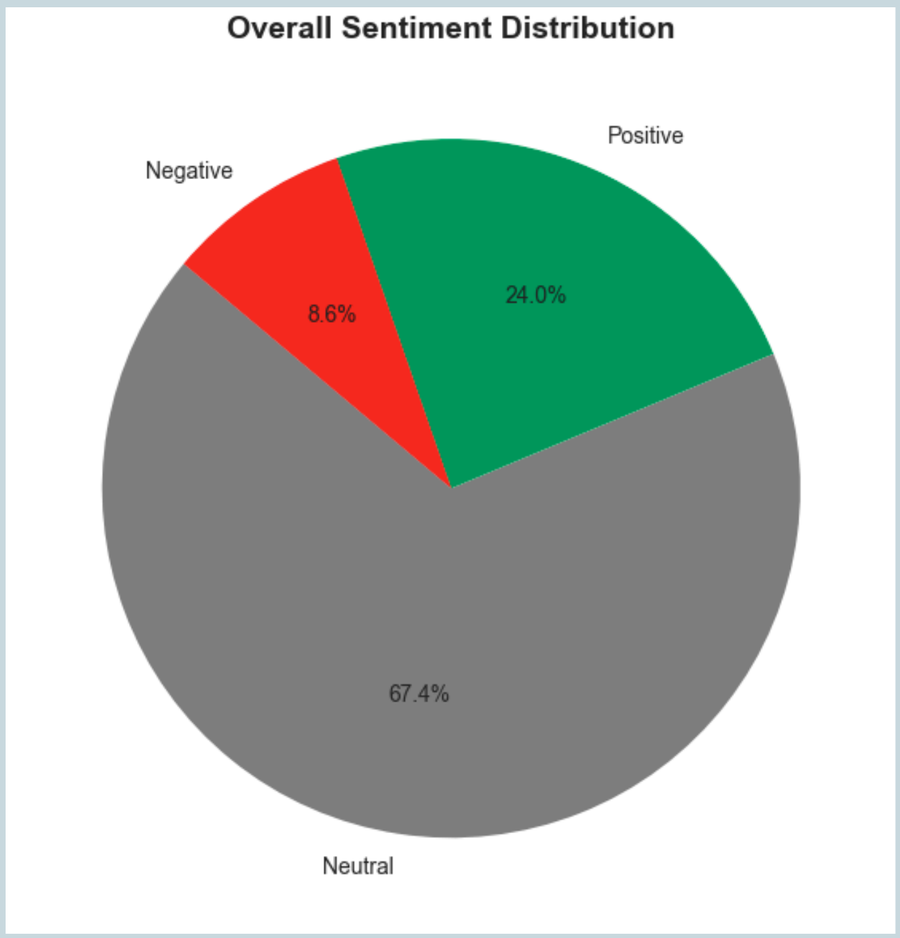
Sample Differences

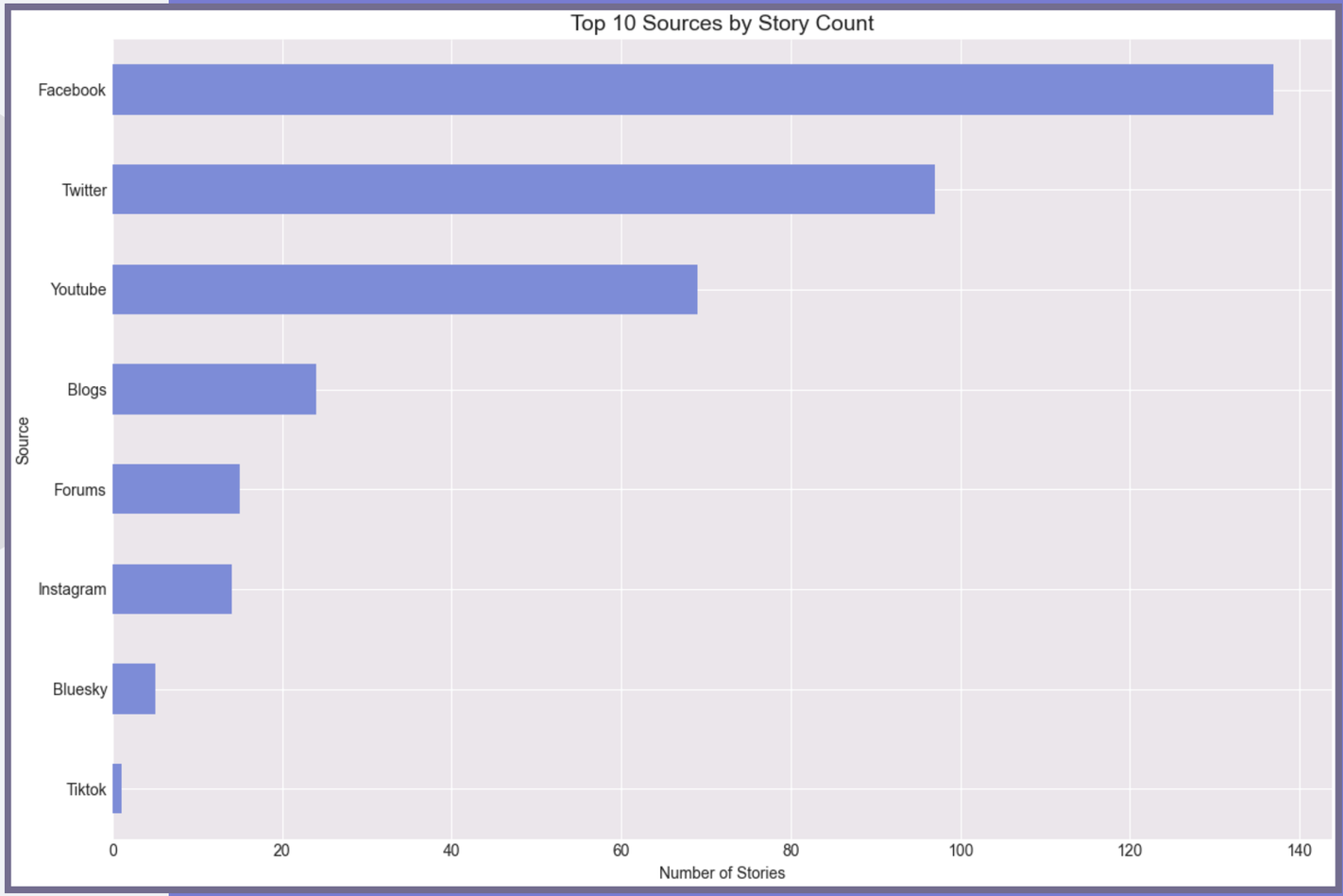
```
Headline: French President Emmanuel Macron Said His Country Would Formally Recognize A Palestinian State During A Un Meeting In September, The Mos
Original Sentiment: Neutral
New Sentiment: Positive
------------------------------------------------------------
Headline: Nearly 500K Families Affected As ‘Crising,’ Habagat Batter Philippines
Original Sentiment: Negative
New Sentiment: Neutral
------------------------------------------------------------
Headline: Pco Approves Removal Of Net 25 Reporter Eden Santos Over Protocol Violations
Original Sentiment: Negative
New Sentiment: Neutral
------------------------------------------------------------
Headline: 🔴Kakapasok Lang Atty. Acosta Ipalit Sa Pco Malacanang Claire Castro Vs Eden Santos Pinakita Palpakan
Original Sentiment: Unknown
New Sentiment: Neutral
------------------------------------------------------------
Headline: Pco Claire Binuking Ni Eden Sa Listahan Ng Drug Free Barangay❗ #Duterte #Bbm #Philippines #Ofwlife
Original Sentiment: Unknown
New Sentiment: Positive
------------------------------------------------------------
```

Trend Visualization

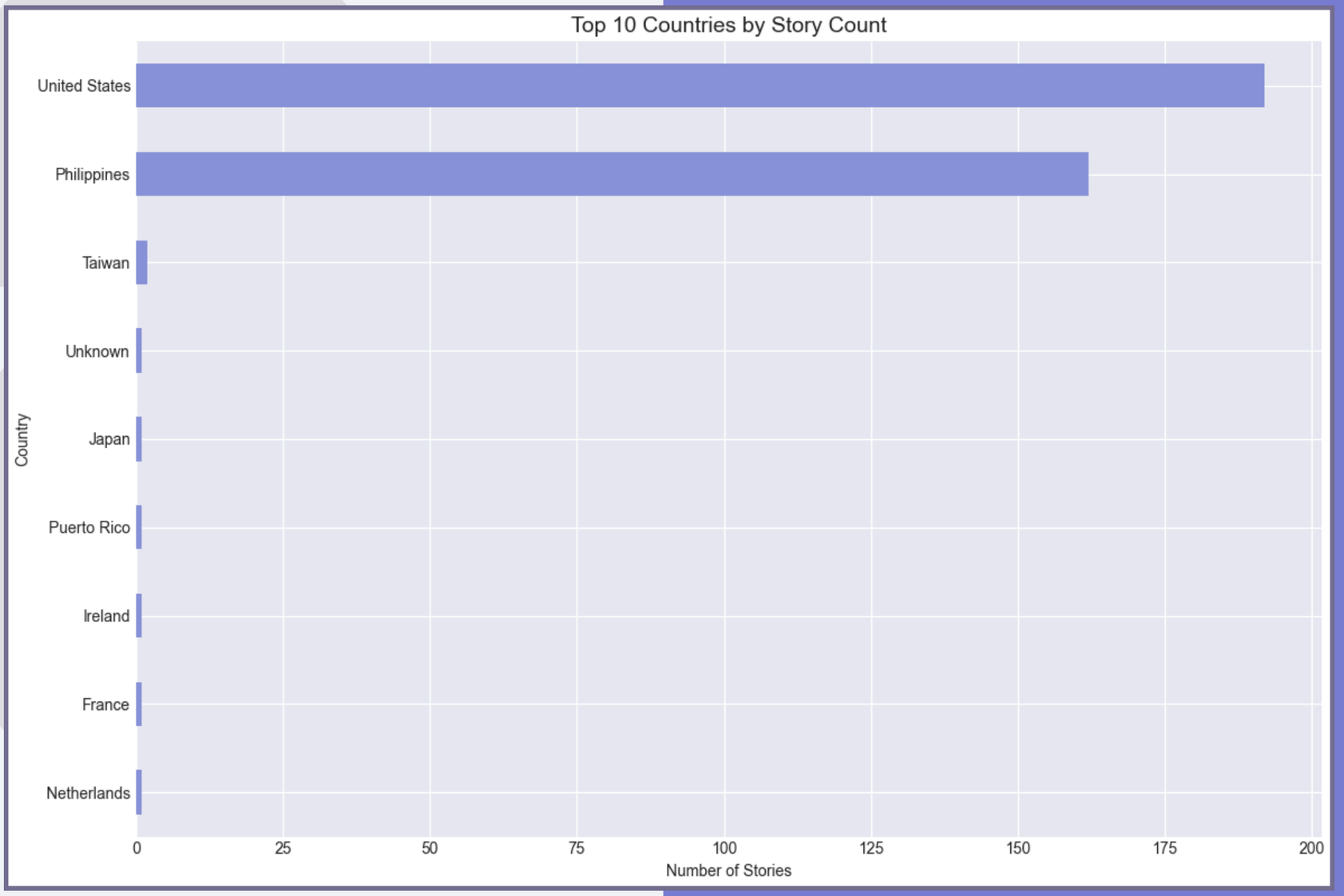


Trend Visualization

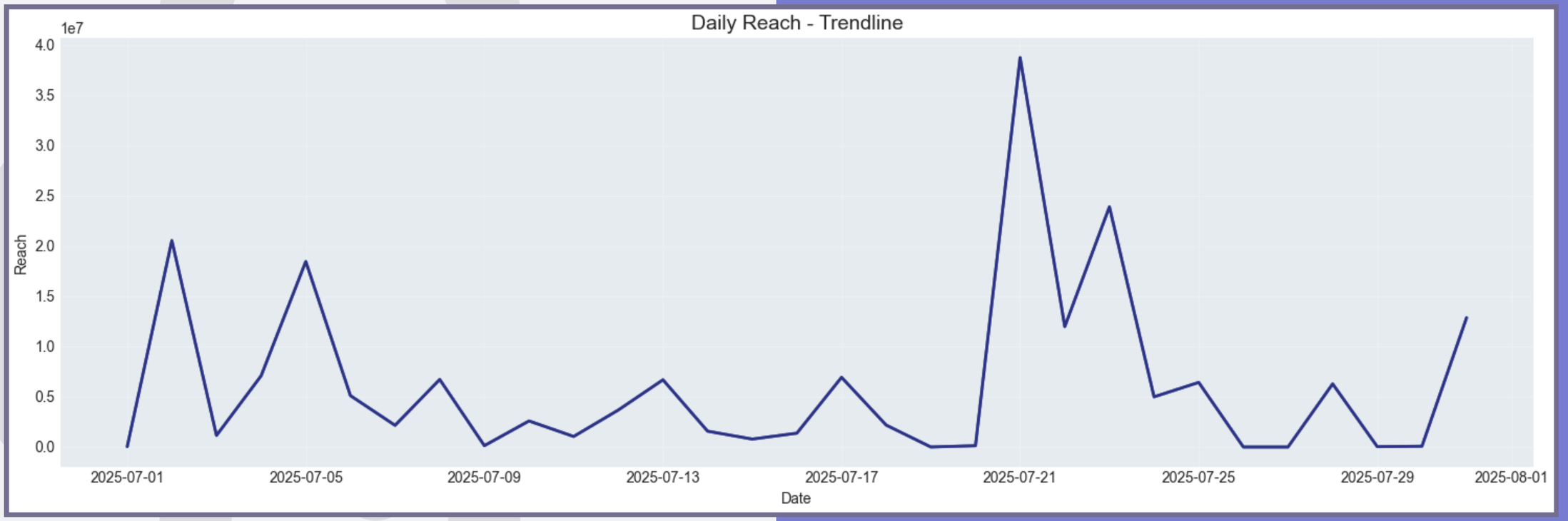




Trend Visualization



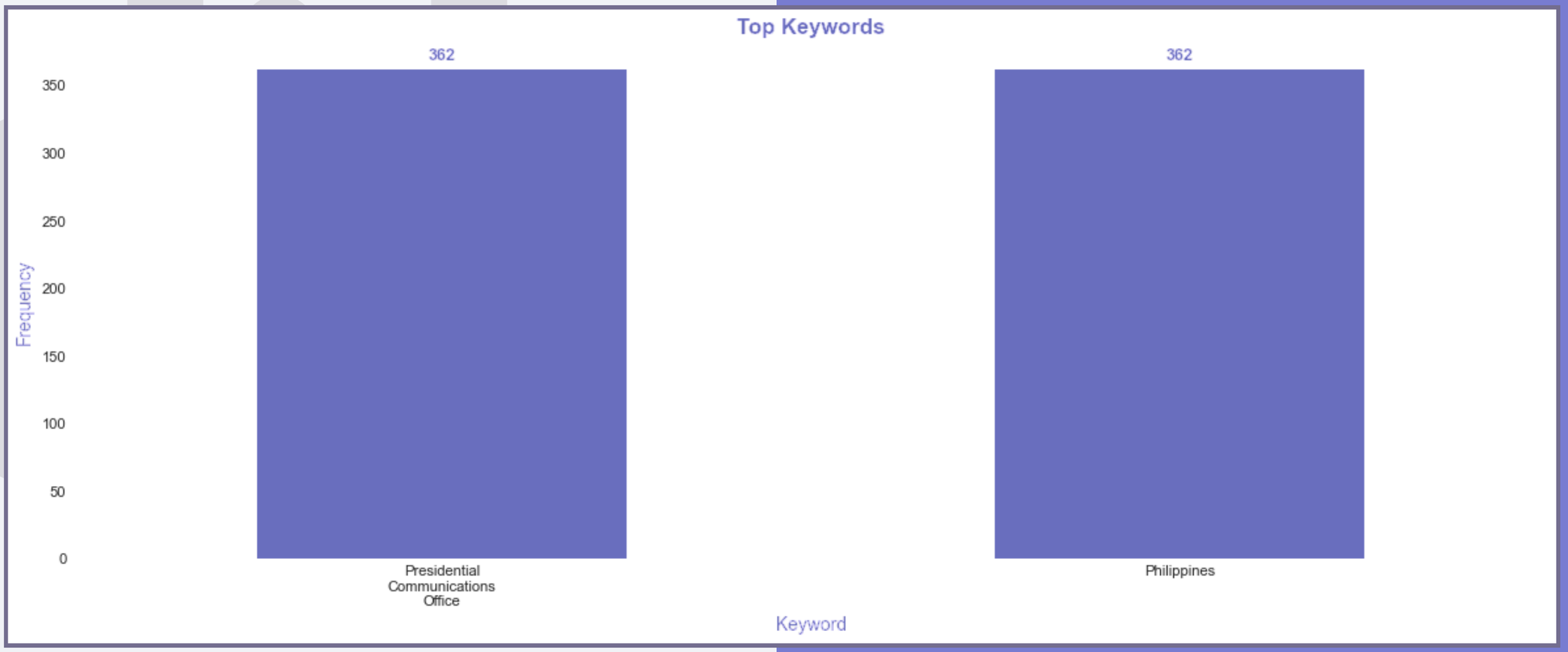
Trend Visualization



*no value for social echo

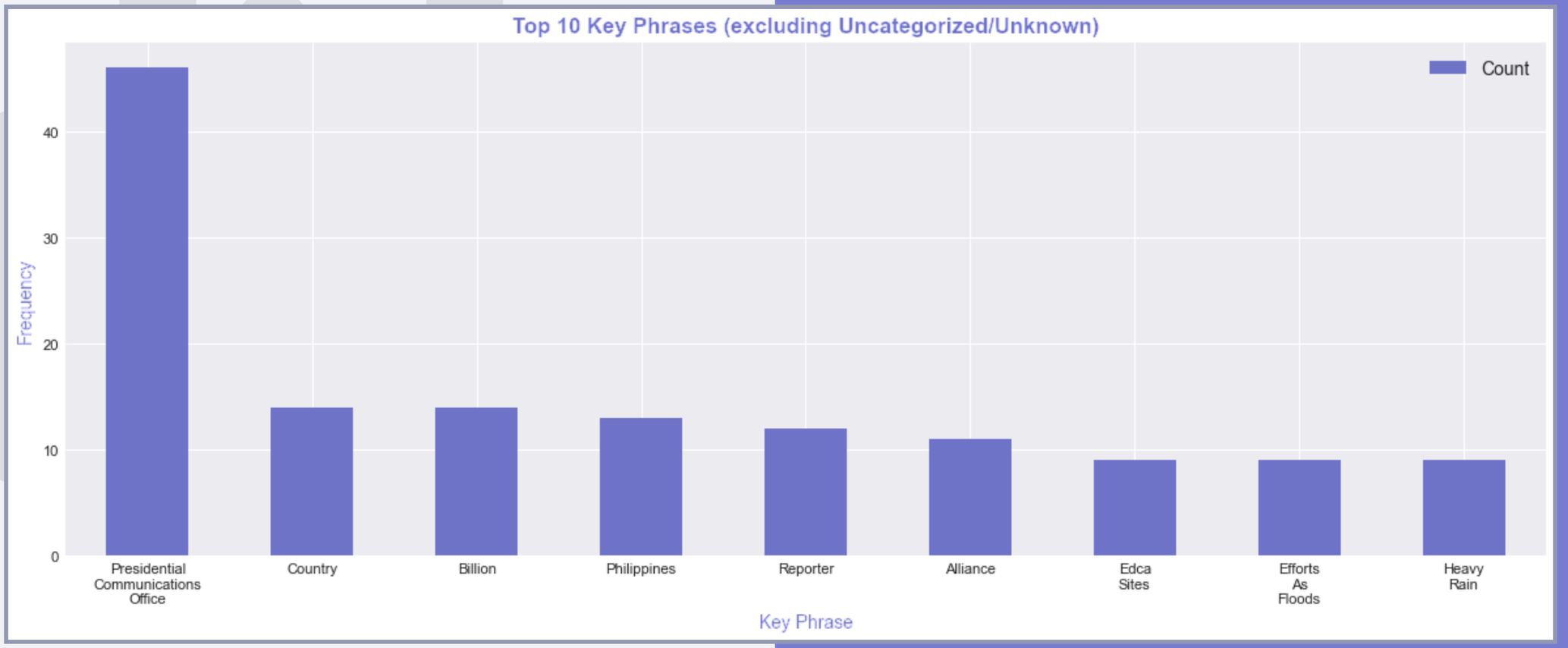
Topic Identification

Content Analysis - Top 10 Common Keywords



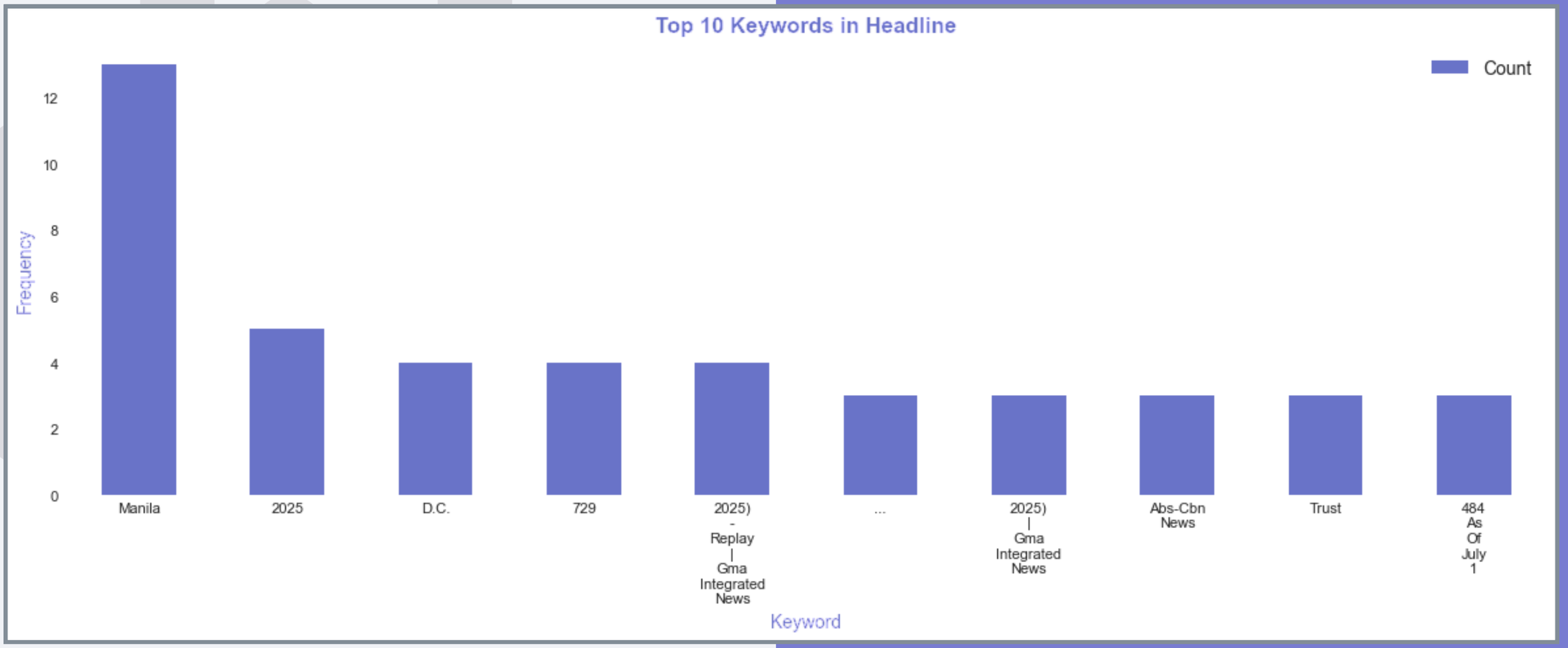
Topic Identification

Content Analysis - Top 10 Key Phrases



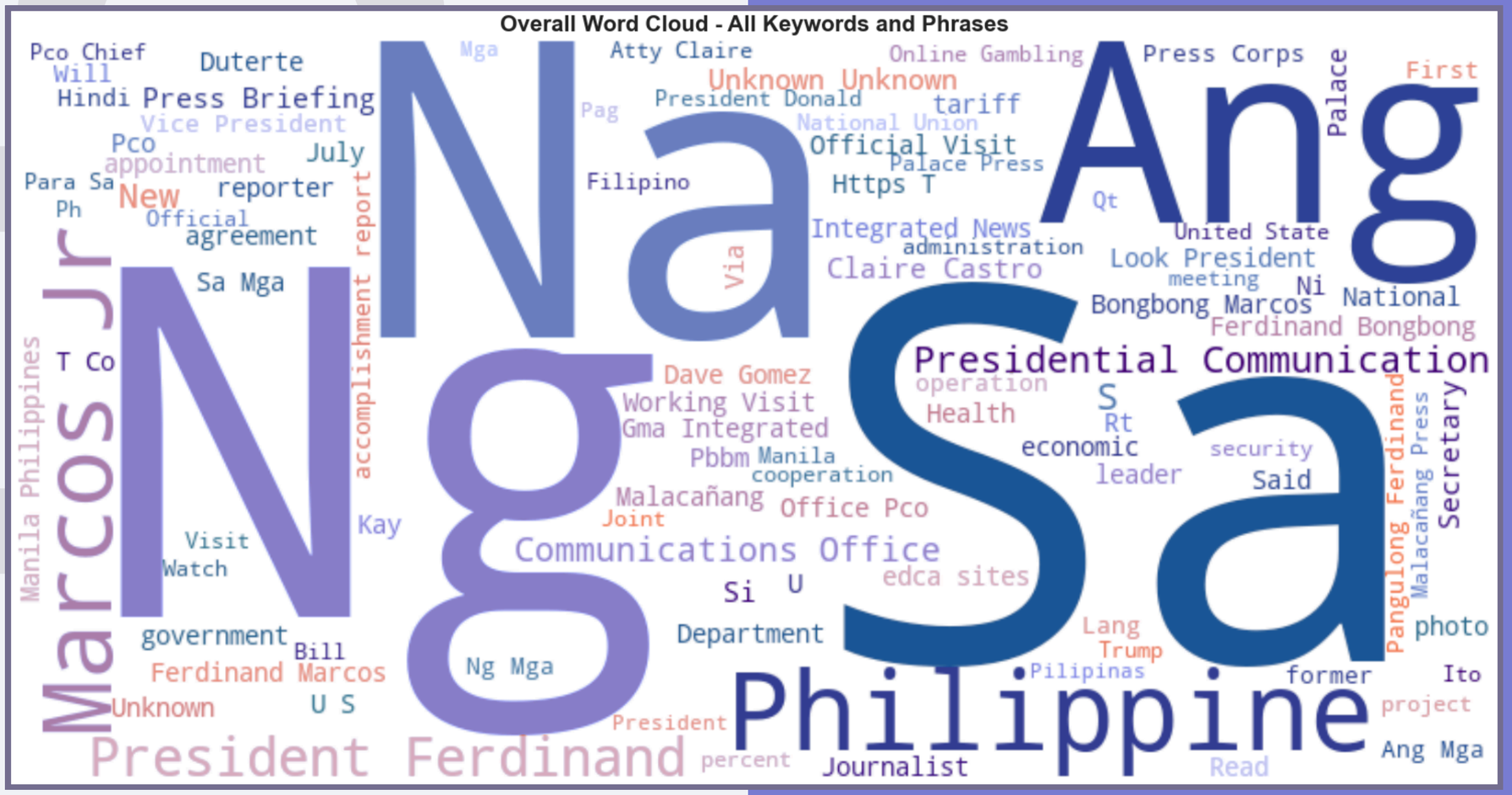
Topic Identification

Content Analysis - Top 10 Keywords in Headline



Word Cloud Visualization

Visual Analysis - All Keywords and Phrases



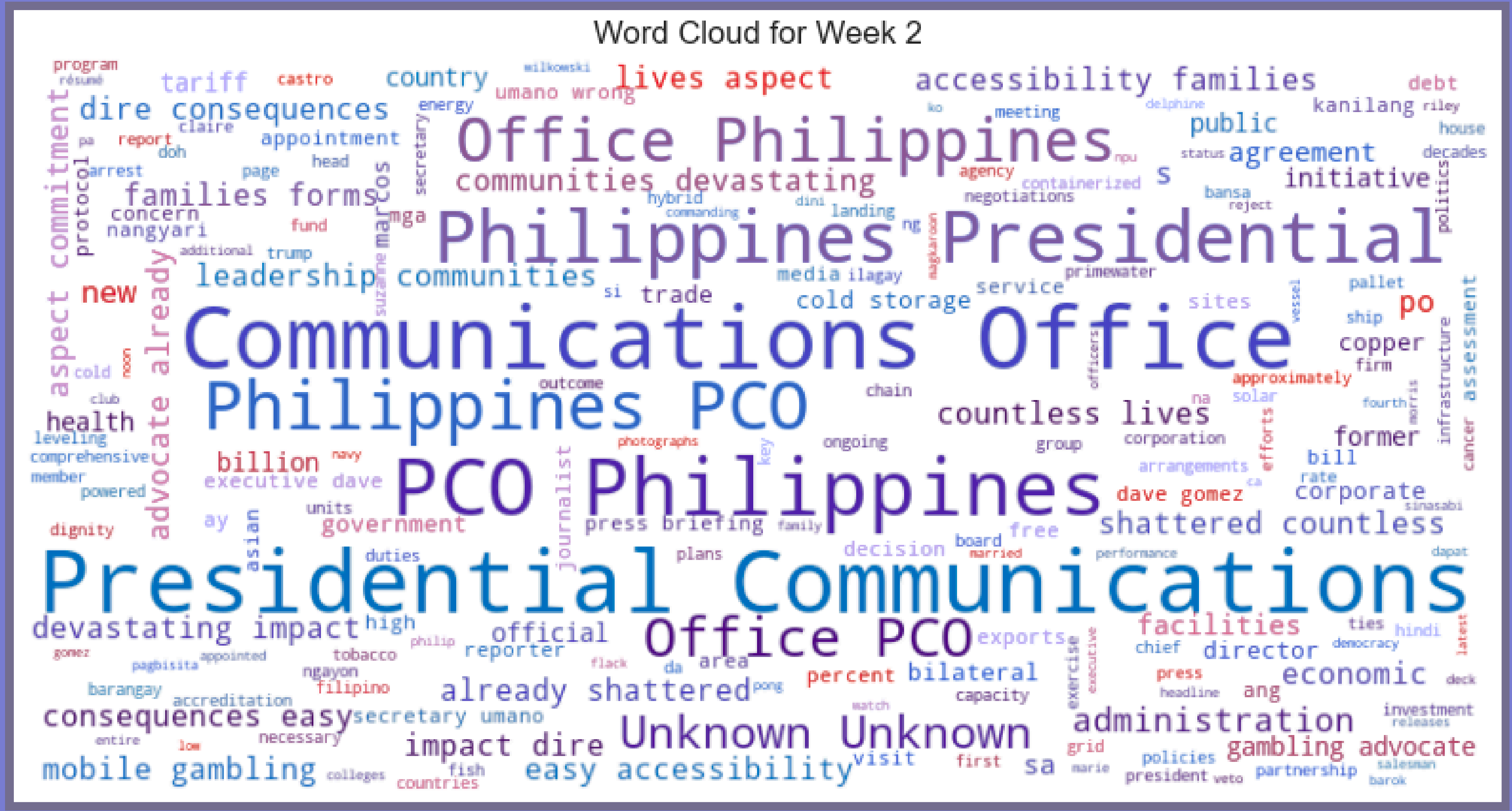
Word Cloud Visualization

Visual Analysis - All Sentiment Categories

Word Cloud Visualization

Visual Analysis - Week 1 vs Week 2

Week 1

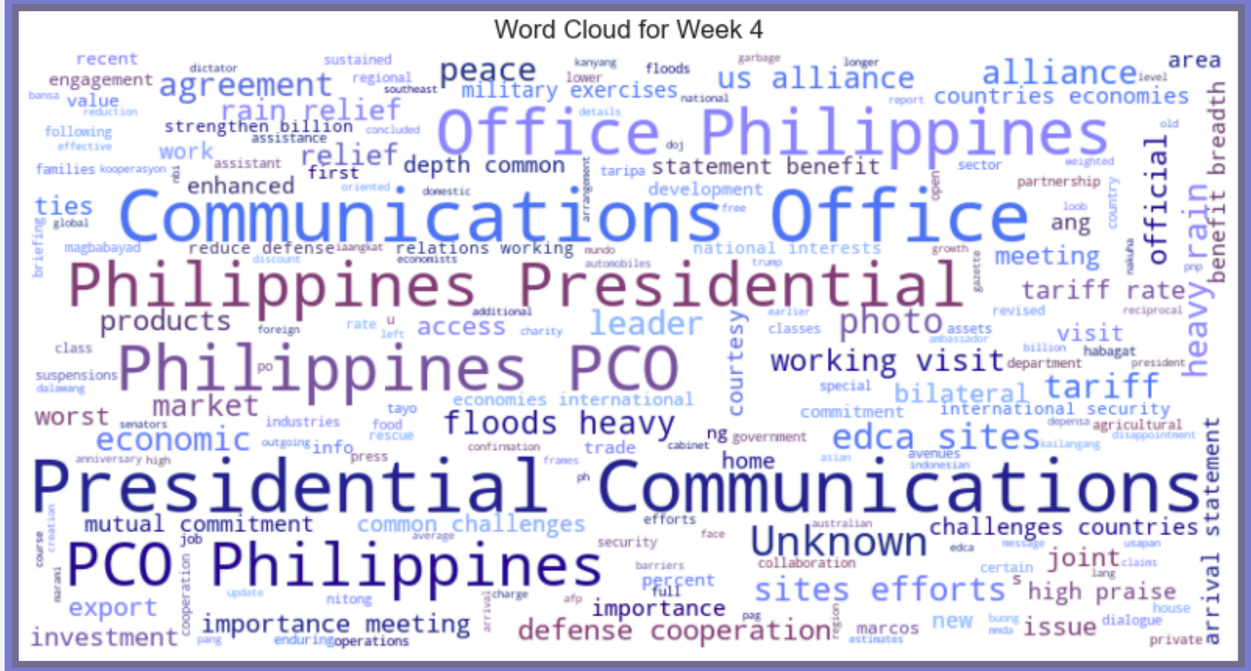


Week 2

Word Cloud Visualization

Visual Analysis - Week 3 vs Week 4

Week 3



Week 4

Word Cloud Visualization

Visual Analysis - Week 5

Week 5

Findings

Which are the top 5 sources by number of stories?

Source	Volume
1. Facebook	137
2. Twitter/X	97
3. YouTube	69
4. Blogs	24
5. Forums	15

Findings

Which country has the most positive sentiment stories?

Country	Volume
1. United States	50
2. Philippines	35
3. Taiwan 3. Netherlands	1

Findings

What's the most common keyword/topic?	Volume
Philippines, Presidential Communications Office	362
Which source has the highest average reach?	**Reach**
Forums	1,224,157
Facebook	1,024,418

SUMMARY INSIGHTS

The Presidential Communications Office (PCO) generated 585 mainstream media (MSM) and 362 social media (SM) coverages in July 2025. Among MSM outlets, Philippine Daily Inquirer accounted for the largest share at 10% (60 articles). On social media, Facebook emerged as the dominant platform with 38% (137 posts), driving much of the critical discourse—particularly surrounding the President's silence on the issue of renewing the Philippines' membership in the ICC.

The Philippines recorded the highest number of positive sentiment stories across both MSM and SM, driven largely by coverage of Communications Secretary Dave Gomez's directive to conduct a performance audit of PCO officials—a move seen as strengthening the government's communication strategy and rebuilding public trust.

SUMMARY INSIGHTS

“Philippines” stood out as the most frequently discussed topic across both media types. Coverage peaked in Week 3 for MSM and in Week 2 for SM, reflecting differences in reporting timelines and public engagement patterns.

In terms of reach, MSN led MSM platforms, with notable coverage of Undersecretary Claire Castro’s call to respect the Supreme Court’s decision to withhold the Vice President’s impeachment trial, while underscoring that a new impeachment complaint could still be filed starting February next year. On social media, Facebook again registered the highest average reach, driven by discourse on the President’s continued silence over ICC membership renewal.

DATA CLEANING DIFFERENCE

DATA CLEANING STEPS	MSM	SM	DIFFERENCE
Load and Deduplicate	Drops duplicates by Source Link, removes rows missing, Date, Headline, Source, Country	Drops duplicates by Source Link, removes rows missing Date, Source, Country	MSM requires Headline to exist; SM allows it to be filled later.
Fix Missing Headline	Keeps rows only if Headline exists	Uses Opening Text as Headline if original is missing/blank	SM is more flexible in filling missing headlines
Date Standardization	Uses Date or Alternate Date Format, cleans into MM-DDYYYY format	Same logic	No major difference

DATA CLEANING DIFFERENCE

DATA CLEANING STEPS	MSM	SM	DIFFERENCE
Source Normalization	Removes www, .com/.ph/.org/.net; maps known acronyms (ABS, CBN, MSN, PTV)	Same cleaning, but: if contains "reddit" → grouped as "Forums"	SM groups Reddit differently, MSM keeps acronyms.
Headline Normalization	Lowercase → remove punctuation → trim → remove duplicate headlines	Same logic	No major difference
Fill Missing Text Fields	Fills Opening Text, Influencer, Key Phrases with "Unknown"	Fills Opening Text, Influencer, Key Phrases, Language, Sentiment with "Unknown"	SM has extra fields (Language, Sentiment)

DATA CLEANING DIFFERENCE

DATA CLEANING STEPS	MSM	SM	DIFFERENCE
Numeric Fields	Converts Twitter/Facebook/Reddit Social Echo to integers, computes Social Echo Total	Same, but also cleans Reach column	SM includes Reach cleaning
Filtering Unwanted Rows	Removes rows with "content from this publisher", "test", "proquest", empty links, and [Courtesy:]	Same filtering rules	No major difference
Drop Columns	Removes metadata columns (social stats, IDs, tags, etc.)	Same logic	Almost identical

DATA CLEANING DIFFERENCE

DATA CLEANING STEPS	MSM	SM	DIFFERENCE
Final Text Cleaning	Country → title case. - Headline → title case. - Opening Text/Hit Sentence → capitalized	Same process	No major difference
Reorder Columns	Moves Clean Date to the first column	Same process	No major difference
Key Phrases and Keyword Column Standardization	Combine the values in the Key Phrases and Keywords columns into a single standardized word, treating them the same regardless of whether they’re in lowercase, uppercase, or mixed case.	Same logic	No major difference

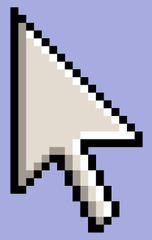
DATA CLEANING DIFFERENCE

DATA CLEANING STEPS	MSM	SM	DIFFERENCE
Country and Language Column Text Data Imputation	Fill in only the blank cells in the Country and Language columns using the language detected from the Hit Sentence, without changing the existing values.	Same logic.	No major difference
Output	Saves as MSM_cleaned.xlsx.	Same logic	No major difference


QUALITY CONTROL
CHECKLIST

Sampling and Spot Checks

Check rows for formatting, alignment, and key details.



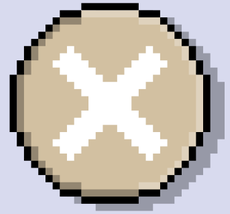
Edge Cases

Ensure missing or duplicate data is handled, dates are valid, and special characters display correctly.

Consistency

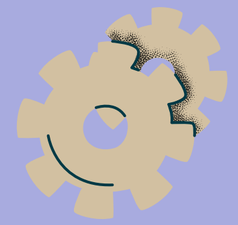
Ensure data structure, validity, and consistency are maintained.

Error Handling



Logs errors and warnings clearly, ensures no rows are skipped silently, and captures exceptions with sufficient detail.

Automation and Reproducibility



Script produces consistent results, edge cases pass, and data-handling assumptions are documented.

Reporting Issues

Log issues with examples, categorize by severity, and escalate unresolved ones before sign-off.

Limitations

Accuracy of Results

Results depend on the quality of raw data; gaps, errors, and bias may still remain despite cleaning.

Rule-Based Constraints

Rule-based cleaning may miss anomalies, and Python libraries have performance and interpretability limits

Text Ambiguity

Text data is ambiguous; sentiment analysis cannot fully interpret tone or sarcasm.

Scalability Challenges

Scaling to larger datasets may pose performance challenges without further optimization.

Recommendations

1

Prioritise Vectorised Operations

Prioritise vectorised operations in Pandas, as they replace Python loops with optimised C-based processes, greatly speeding up repetitive data-cleaning tasks and improving scalability (Compile N Run, n.d.).

2

Employ Data Type Optimisation

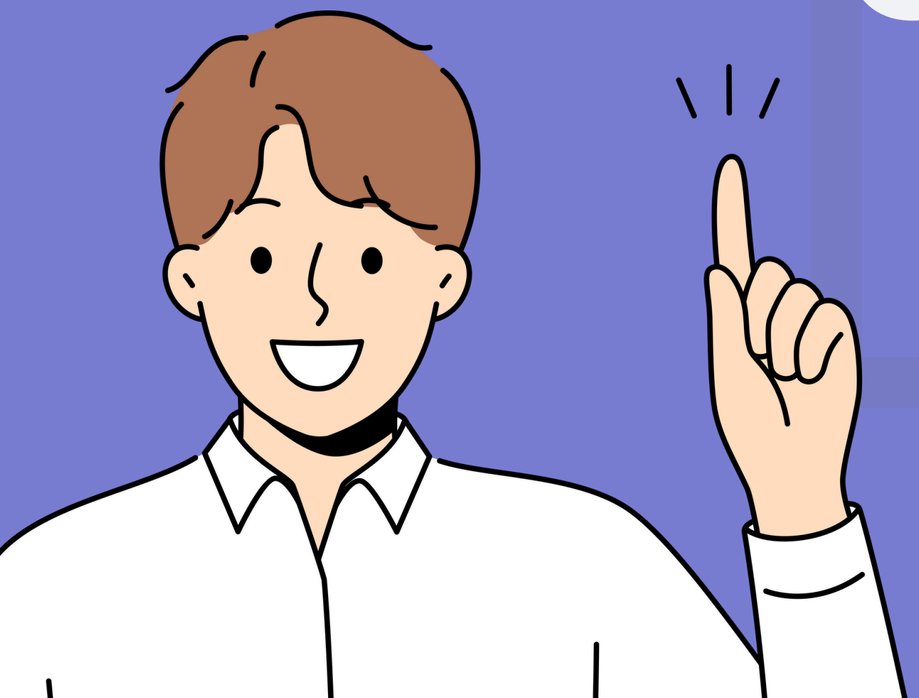
Downcasting numerical columns (e.g. float64 to float32) and converting repeated-value object columns to categorical types can reduce memory usage by up to 80% without affecting accuracy (GeeksforGeeks, 2023a).

3

Utilise Chunk-Based Processing for Large Datasets

Use chunk-based processing (e.g. pd.read_csv(..., chunksize=100000)) to handle large datasets efficiently, reducing RAM use and enabling scalable cleaning of millions of records (GeeksforGeeks, 2023b).

Conclusion



This project successfully demonstrated the capability of the team’s data pipeline to process, clean, and analyze information from multiple sources. The code performed reliably, executing the workflow from data ingestion to visualization with consistency. It effectively managed duplicate removal, standardization, and dataset separation, while also producing sentiment analyses and keyword visualizations. Although limitations remain, particularly with textual ambiguity and scalability for larger datasets, the test confirms that the methodology is **sound** and **provides a strong foundation for future refinement and broader application**.

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THANK
YOU
LORD!!