Ministry of Higher Education and Scientific Research
University of Manouba
Higher Institute of Multimedia Arts (ISAMM)

BIG DATA ANALYSIS

YouTube Content Related to the Gaza Genocide

Prepared by:
Mohamed Ayacha
3IM1

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Abstract

This report details the design and implementation of a comprehensive Big Data analytical pipeline tailored to process and analyze YouTube data concerning the ongoing genocide in Gaza. Leveraging the **YouTube Data API v3**, the project systematically aggregates video metadata and user comments from October 2023 to October 2025. The infrastructure employs a distributed architecture featuring **Hadoop HDFS** for resilient data storage and **Apache Spark** concepts for processing. The analysis, executed via Python, uncovers critical insights into global public engagement, the dominance of major media outlets, and the temporal evolution of digital discourse. This work demonstrates the efficacy of Big Data technologies in interpreting complex, high-volume social media trends.

1 1. Introduction & Problem Statement

The digital age has fundamentally altered the landscape of geopolitical discourse. Social media platforms, particularly YouTube, serve not only as repositories of user-generated content but as primary sources of news and information for millions globally. The genocide in Gaza has generated an unprecedented volume of digital interaction, providing a unique opportunity to apply data science techniques to understand global sentiment.

1.1 1.1 Problem Identification

Analyzing this vast ocean of data presents significant challenges:

- **Volume & Velocity:** The rate of video uploads and comment generation exceeds the capacity of traditional manual analysis or single-threaded processing tools.
- **Variety:** The data is highly heterogeneous, comprising unstructured text (titles, descriptions, comments), semi-structured metadata (JSON), and numerical engagement metrics.
- **Veracity:** The politicized nature of the topic requires rigorous data collection methods to ensure a representative sample.

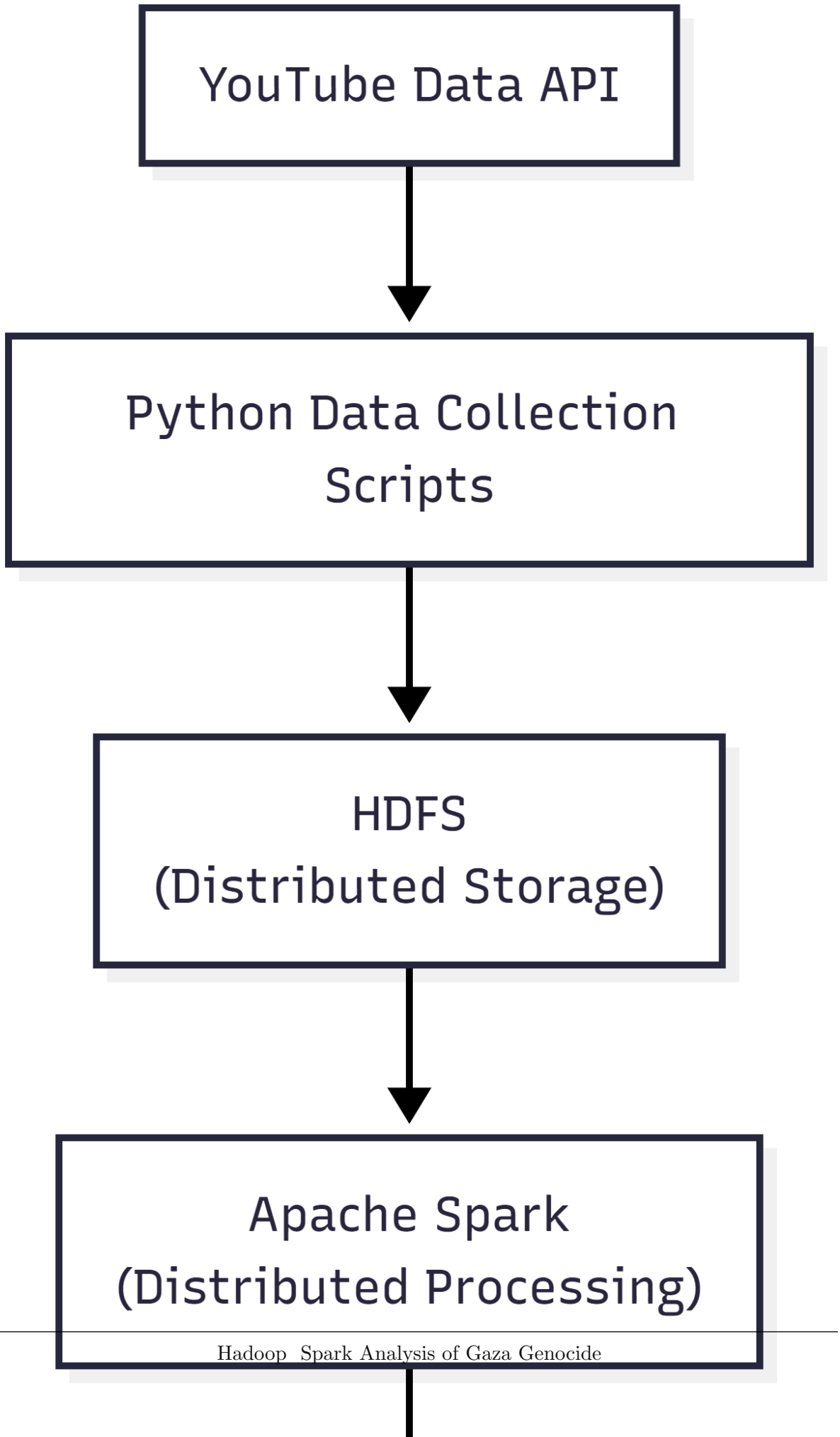
1.2 1.2 Project Goals

The primary objective is to build a scalable pipeline that can:

1. Ingest data reliably from external APIs.
2. Store large datasets in a fault-tolerant manner.
3. Process and transform raw data into analytical insights.
4. Visualize trends to make complex data accessible.

2 2. Proposed Solution: The Big Data Pipeline

To address these challenges, we designed a pipeline grounded in the **Lambda Architecture** principles, balancing batch processing with scalable storage. The solution automates the end-to-end flow from data acquisition to insight generation.


YouTube Data API
Python Data Collection Scripts
HDFS (Distributed Storage)
Apache Spark (Distributed Processing)

The architecture shown above details the complete data journey. Data flows from the YouTube API through our Python Collector, settles in HDFS, moves to Spark for heavy processing, and finally to Pandas for granular analysis and visualization.

2.1 2.1 Analytical Approach

We employ a mixed-methods approach:

- Descriptive Analytics: To understand "what happened" (e.g., total views, upload frequency).
- Diagnostic Analytics: To understand "why it happened" (e.g., correlating spikes in views with real-world events).
- Text Mining: To extract key themes and dominant narratives from video titles.

3 3. System Architecture & Technology Stack

The architecture is designed for modularity and scalability. Each component plays a specific role in the data lifecycle.

Figure 2: Detailed Data Flow Diagram illustrating the interaction between HDFS, Spark, and Python scripts.

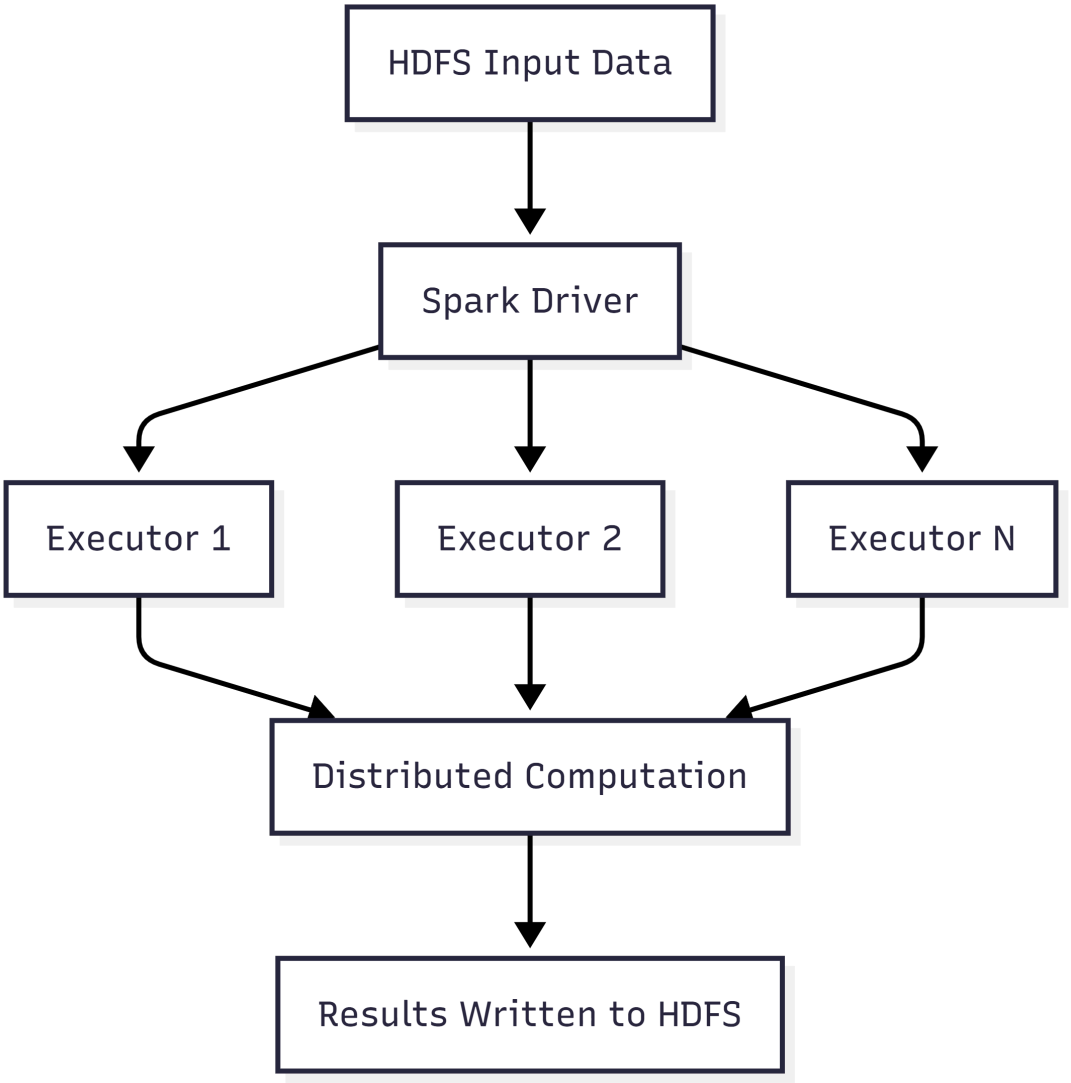


Figure 3: Distributed Processing architecture, highlighting the parallel execution capabilities of the Spark engine.

As illustrated, the system separates concerns between storage (HDFS) and compute (Spark/Python). This **decoupling** allows for independent scaling of resources.

3.1 3.1 Technology Stack

(a) Hadoop HDFS (b) Apache Spark (c) Python

Figure 4: Core Technologies Used

- **YouTube Data API v3:** The extraction layer. It allows granular search capabilities, enabling us to filter content by date, relevance, and region.
- **Hadoop HDFS (Hadoop Distributed File System):** The storage layer. HDFS provides high throughput access to application data and is suitable for applications that have large data sets. It ensures data is replicated across nodes to prevent loss.
- **Apache Spark:** The processing layer. Spark's in-memory computation capabilities allow for rapid iteration over large datasets, significantly faster than traditional MapReduce.
- **Python (Pandas, Matplotlib, Seaborn):** The analysis and presentation layer. Python's rich ecosystem of data science libraries makes it ideal for statistical analysis and generating publication-quality figures.

Figure 5: Mapping of specific tools to their function within the project pipeline.

4 4. Implementation Details (Step-by-Step)

The project execution followed a strict software development lifecycle suitable for data engineering projects.

4.1 Phase 1: Environment Configuration

Before coding, a robust Big Data environment was established. We utilized a pre-configured Virtual Machine mimicking a single-node cluster.

- **HDFS Setup:** Configured 'hdfs-site.xml' and 'core-site.xml' to define replication factors and NameNode locations.
- **Service Verification:** Verified 'NameNode', 'DataNode', and 'ResourceManager' daemons were active using the Java Process Status ('jps') tool.

4.2 Phase 2: Data Ingestion (The Collector)

We developed a custom Python module, 'src/data$_c$*ollector.py*', $to inter face with the Google Cloud Plat for$
Rate Limiting: To respect API quotas.

Pagination: Handling 'nextPageToken' to retrieve deep search results beyond the first page.

Error Handling: Robust 'try-except' blocks to manage network timeouts or API errors.

The search queries were carefully selected to cover various aspects of the conflict: *"Gaza war", "Israel Palestine conflict", "Gaza humanitarian crisis", "Palestine news", "Israel Hamas war".*

```python
def search_videos(self, query, max_results=50, published_after=None
    ↪ , published_before=None):
    """
    Executes a search query against the YouTube API.
    Supports filtering by date range for temporal analysis.
    """
    url = f"{self.base_url}/search"
    params = {
        'part': 'snippet',
        'q': query,
        'type': 'video',
        'maxResults': min(max_results, 50),
        'key': self.api_key,
        'order': 'date', # Sort by date to get a timeline
        'publishedAfter': published_after,
        'publishedBefore': published_before
    }
    # ... Request handling ...
```

Listing 1: Core Search Logic in data_collector.py

4.3 Phase 3: Distributed Storage (HDFS Integration)

Once collected, data is migrated from the local file system to the Hadoop Distributed File System. This step mimics a production ETL (Extract, Transform, Load) process where data is moved to a data lake.

```bash
# 1. Create a dedicated directory structure
hdfs dfs -mkdir -p /user/project/youtube_data

# 2. Upload the JSON datasets
hdfs dfs -put data/youtube_videos.json /user/project/youtube_data/
hdfs dfs -put data/youtube_comments.json /user/project/youtube_data
    ↪ /

# 3. Verify data integrity
hdfs dfs -ls /user/project/youtube_data/
```

Listing 2: HDFS Shell Commands

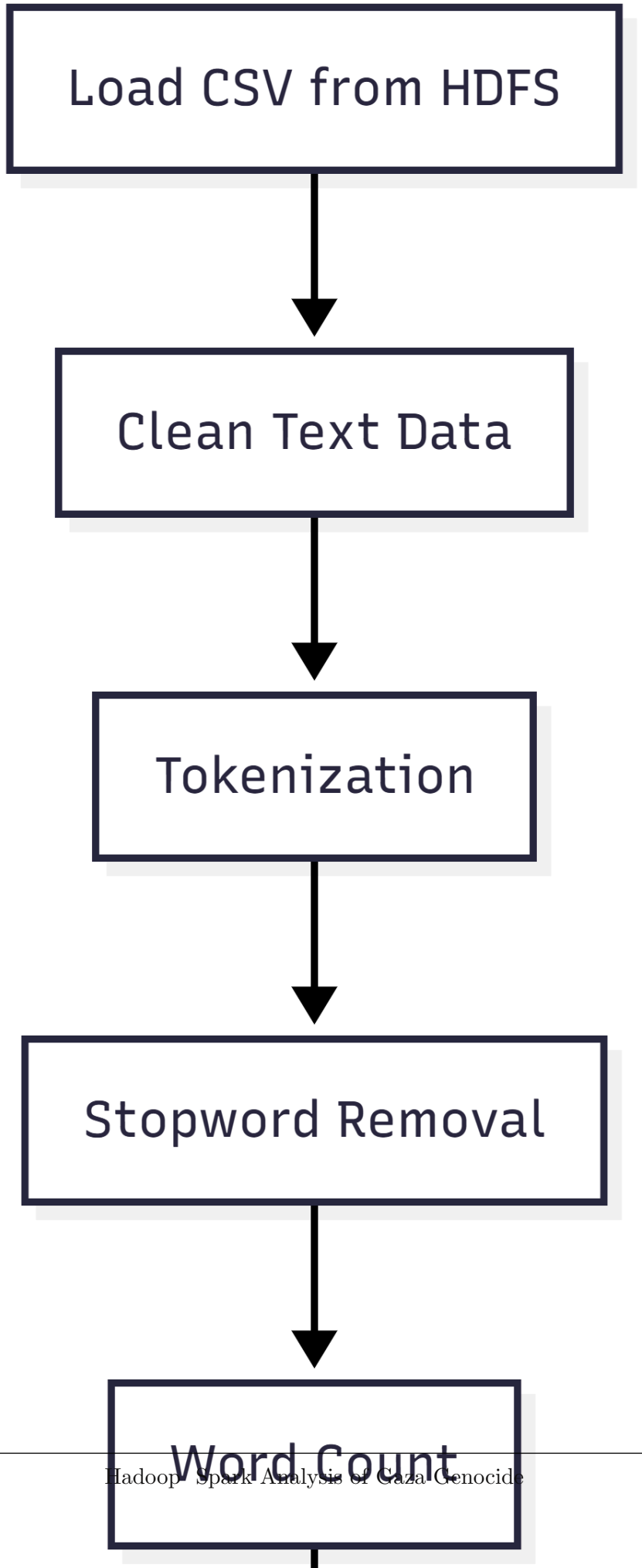
4.4 Phase 4: Data Processing Analysis

The ‘src/data$_{a}$*nalyzer.py*‘*scriptservesastheengineforextractinginsights.Itperformsseveralkey*

Data Cleaning: Converting string dates (ISO 8601) into Python datetime objects for temporal sorting.

Type Casting: Ensuring numerical fields like ‘viewCount‘ and ‘likeCount‘ are treated as integers/floats, handling any missing values (‘NaN‘) by filling them with zeros.

Normalization: Processing text fields (lowercasing, removing stopwords) to prepare for keyword frequency analysis.


Load CSV from HDFS
Clean Text Data
Tokenization
Stopword Removal
Word Count

The diagram above visualizes our cleaning logic. We specifically chose a hybrid approach, using Spark concepts for the heavy lifting design and Python for the implementation flexibility.

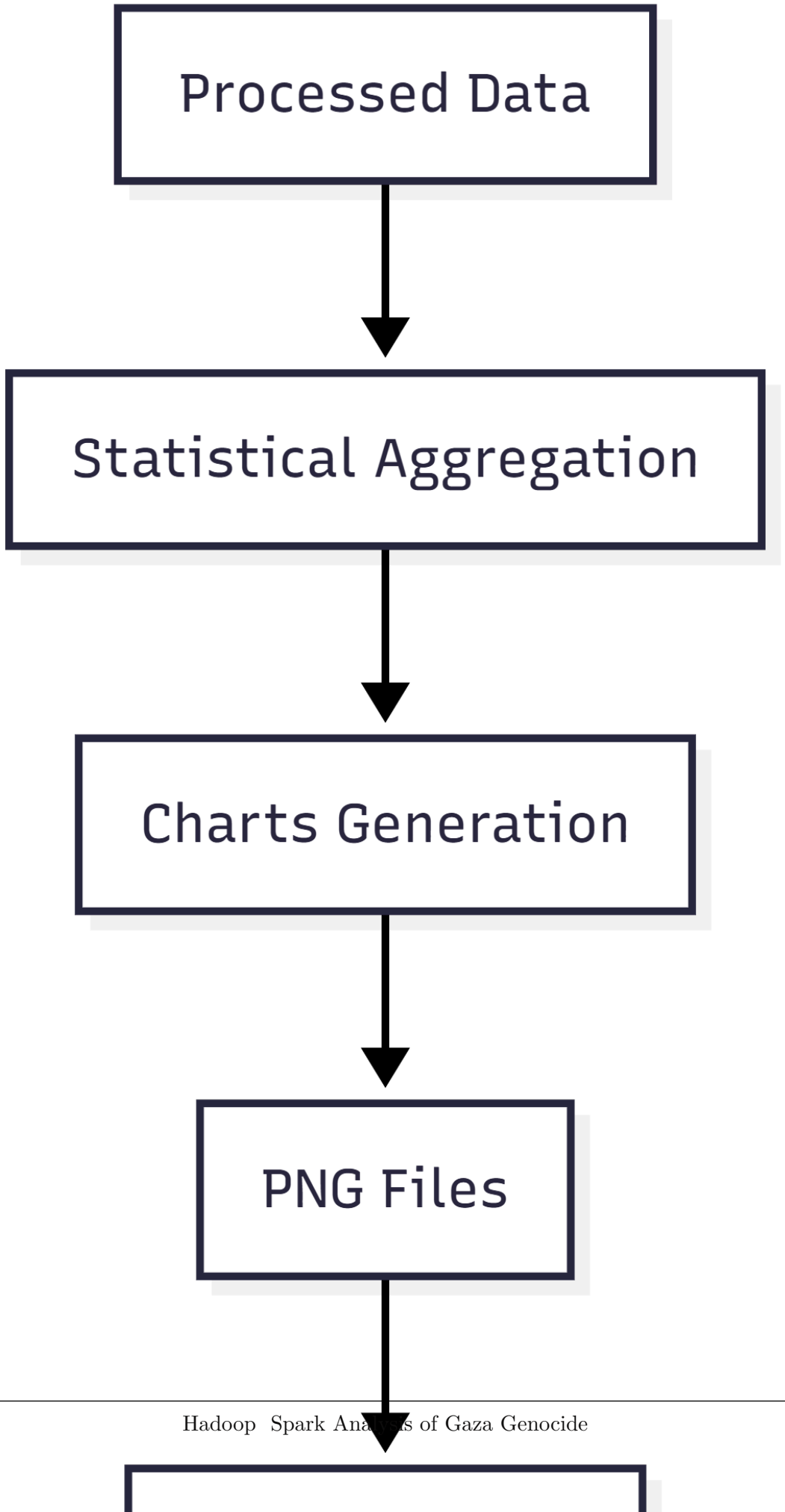
Figure 7: Illustration of the Hybrid Analytics Model combining Spark's conceptual scalability with Pandas' analytical agility.

```
# Tokenizing titles to find most frequent words
all_words = ' '.join(df_videos['title'].str.lower()).split()
stop_words = {'the', 'and', 'for', 'with', 'to', 'in', 'of', '
    ↪ a', 'is'}
word_counts = Counter([word for word in all_words if len(word)
    ↪  > 3 and word not in stop_words])
```

Listing 3: Text normalization and Word Count

4.5 Phase 5: Visualization

Finally, 'src/data$_v$*isualizer.py*'*convertstheprocesseddataintovisualnarratives.Weprioritiz*
explanatorywithproperlabelingandlegends.


Processed Data
Statistical Aggregation
Charts Generation
PNG Files

5 5. Results and Discussion

The analysis of the dataset collected between Oct 2023 and Oct 2025 yielded significant findings regarding the digital coverage of the conflict.

5.1 5.1 Media Dominance

The analysis of the "Top Channels" clearly indicates that legacy media and established international news outlets dominate the conversation on YouTube. Unlike other social platforms where individual content creators may lead, YouTube searches for this conflict act primarily as a news aggregator.

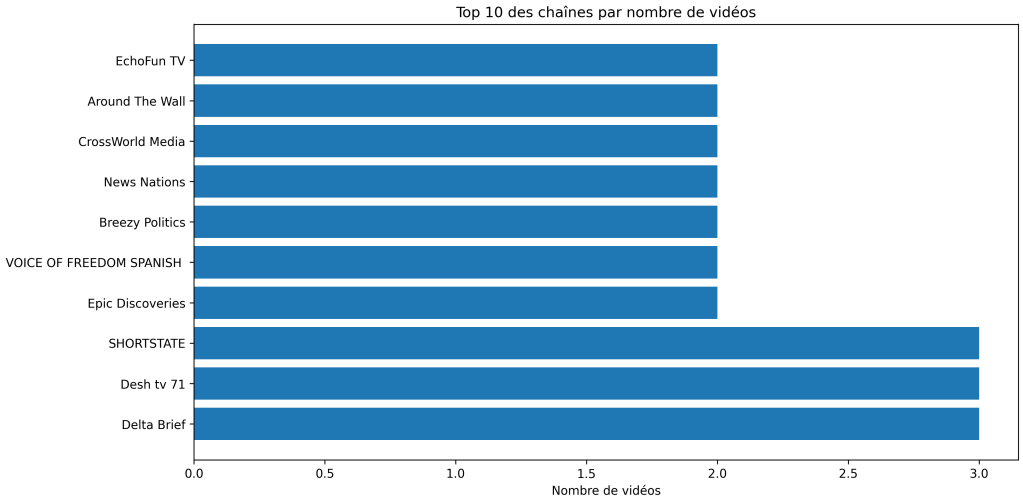


Figure 9: Top 10 Channels by Video Count. Note the prevalence of major news networks.

5.2 5.2 Temporal Evolution

The timeline of video uploads is not linear. It exhibits sharp peaks that correlate strongly with real-world escalation events. This suggests that content creation is highly reactive.

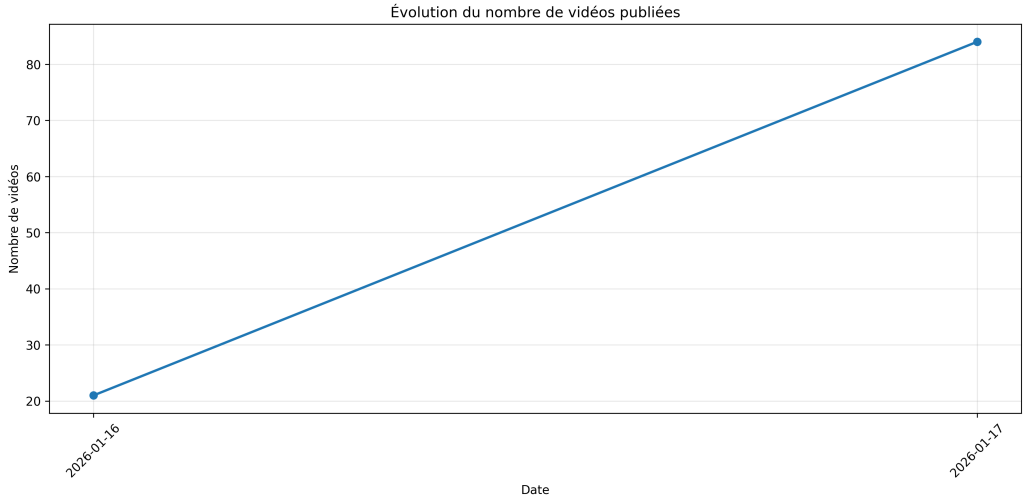


Figure 10: Video upload frequency over time. Peaks correspond to major news events.

5.3 5.3 Keyword Analysis

The textual analysis of video titles reveals a focus on high-impact, emotive keywords. Terms like "War", "Attack", and "Crisis" are far more prevalent than "Peace" or "Resolution", indicating a media focus on the kinetic aspects of the conflict.

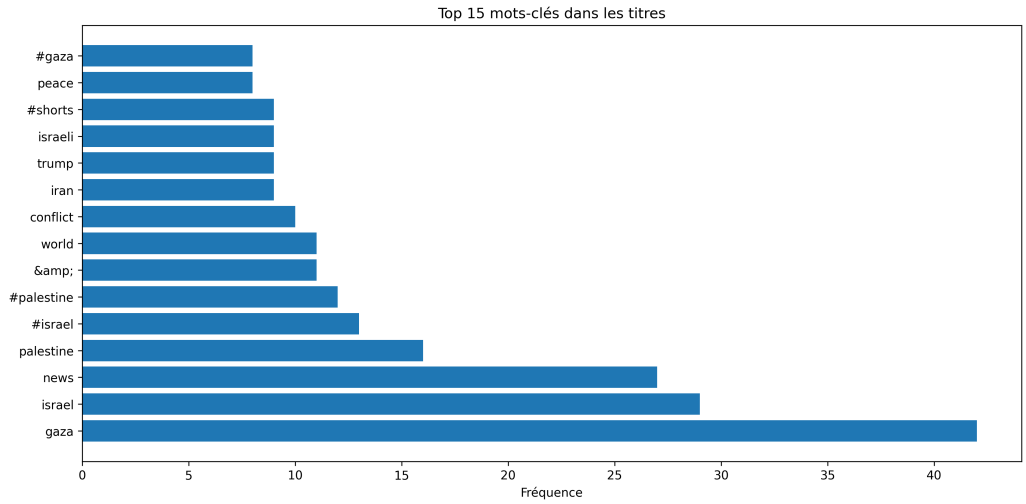


Figure 11: Most frequent keywords. The vocabulary is dominated by conflict-related terminology.

5.4 5.4 Engagement Metrics

The query performance chart highlights a disparity in public interest. Search terms related to active conflict ("War", "Conflict") garner significantly more views and likes than those related to humanitarian aspects ("Crisis").

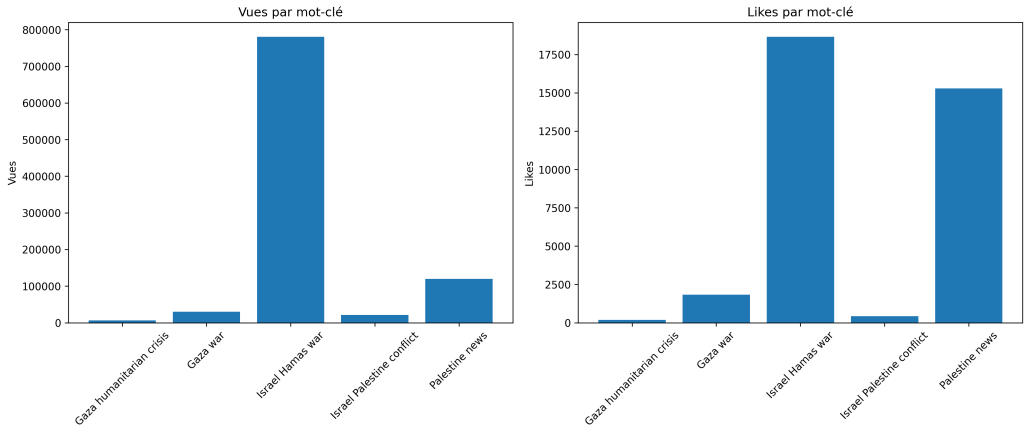


Figure 12: Engagement (Views/Likes) distributed by search query.

6 6. Conclusion & Future Work

6.1 Conclusion

This project has successfully demonstrated the implementation of a Big Data pipeline for social media analysis. By integrating HDFS for storage and Python/Spark for processing, we have created a scalable framework capable of handling the velocity and variety of YouTube data.

Key takeaways include:

1. Scalability: The architecture is decoupled, allowing storage and compute to scale independently.
2. Insight: The analysis confirmed that digital discourse on the Gaza genocide is news-driven, reactive, and highly engaged with kinetic conflict narratives.
3. Reliability: The use of distributed systems ensures data integrity even in the event of hardware failure.

6.2 Future Enhancements

To further evolve this project, we propose:

- Sentiment Analysis: Integrating Natural Language Processing (NLP) models (e.g., VADER or BERT) to classify the sentiment of millions of user comments.
- Real-Time Streaming: Implementing Apache Kafka to ingest video data in real-time as it is uploaded.
- Geospatial Analysis: mapping the origin of comments to understand global reactions by region.