

# **FA 25 6513-C BIG DATA FINAL PRESENTATION**



**LLM DataPrep: Scalable Pipeline for Biomedical  
Fine-Tuning**

**Professor: Amit Patel**

# PROBLEM STATEMENT:

- Biomedical text (PubMed: **2.2M entries**) is **noisy, duplicated, and unstructured**
- Raw data **cannot** be used directly for LLM fine-tuning
- Need a **scalable pipeline** to transform big biomedical datasets into high-quality training data



# DATA OVERVIEW

- Data Source Name: PubMed
- **Data Source Link:** <https://huggingface.co/datasets/MedRAG/pubmed>
- Dataset File Size: 2.78 GB (Parquet) & ~70GB(JSONL)
- Approximate Number of Records: 2.21 Million
- **Columns Include:** id, title, content, contents, PMID

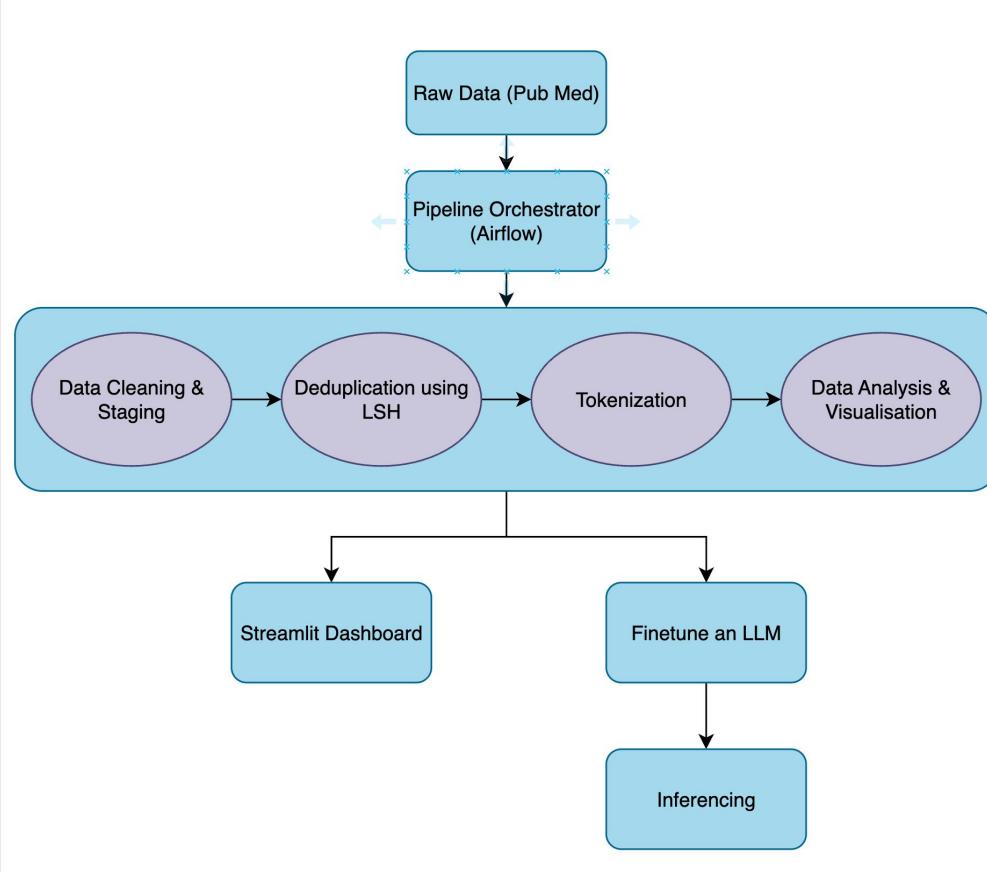
# WHAT TECH STACK WE USED



# PROPOSED SOLUTION

- Build a scalable end-to-end ETL pipeline to process millions of biomedical text records efficiently.
- Automatically clean, normalize, deduplicate, and tokenize PubMed data to produce high-quality training inputs.
- Orchestrate and automate all pipeline stages using Apache Airflow for reliability and repeatability.
- Generate a structured, LLM-ready dataset for domain-specific fine-tuning.

# High Level Pipeline Architecture



# Step 1 - Data Cleaning

```
--- Output of STEP 1: Data Cleaning & Staging ---
STEP 1: Starting Data Cleaning and Staging...
Initial record count: 2209839
Cleaned records saved: 2209839
Stage 1 data written to hdfs:///user/gg3039_nyu_edu/LLM_DataPrep/cleaned/stage1_data
```

- **Loads the raw PubMed text and builds a clean main\_text field by merging and normalizing the content.**
- **Removes noise such as citations, extra spaces, and short/invalid entries.**
- **Saves a cleaned, standardized dataset to HDFS for the next stage.**

# Step 2: Deduplication Using MinHash LSH

```
--- Output of STEP 2: Near-Deduplication (LSH) ---
STEP 2: Starting Near-Deduplication (LSH)...
Records removed by deduplication: 186606
Stage 2 data written to hdfs:///user/gg3039_nyu_edu/LLM_DataPrep/cleaned/stage2_data
```

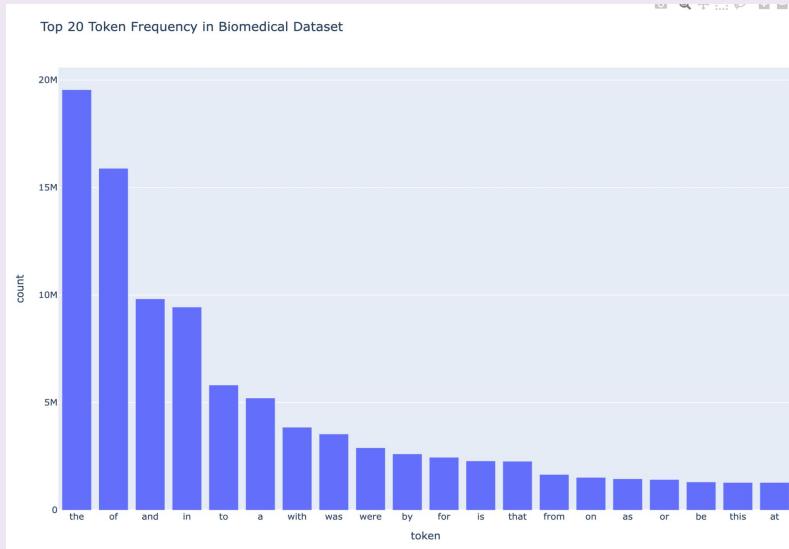
- **Tokenizes each document and converts it into a hashed feature vector using HashingTF, enabling efficient similarity checks.**
- **Uses MinHash LSH to group together texts that are highly similar and flags them as potential duplicates.**
- **Removes these near-duplicate records and saves a cleaned, deduplicated dataset to HDFS while reporting how many were dropped.**

# Step 3: Distributed Tokenization

```
--- Output of STEP 3: Tokenization & Final Save ---
STEP 3: Starting Tokenization and Final Save...
Final records saved: 2023233
Final LLM dataset written to hdfs:///user/gg3039_nyu_edu/LLM_DataPrep/final/llm_dataset
```

- Converts **main\_text** and **title** into numeric token sequences that LLMs use for learning
- Standardizes the dataset to keep only the fields required for downstream LLM training: **id**, **PMID**, **title**, **main\_text**, **tokens**
- Processes tokenization in parallel across the Spark cluster, enabling millions of records to be handled efficiently
- Writes the final structured dataset as Parquet to HDFS for fast retrieval during model fine-tuning
- Produces a terminal summary with the total number of tokenized records

# Step 4: Data Analysis & Visualization



- **Analyzes the cleaned and tokenized dataset to compute basic statistics like total records and average text length.**
- **Identifies the most common tokens in the corpus to understand vocabulary patterns.**
- **Generates an interactive Plotly chart and saves it for visualization and reporting.**

# Data Analysis - Hive Queries

```
VERTICES 04/04 [=====>>>] 100% ELAPSED TIME: 41.06 s
INFO : Completed executing command(queryId=hive_20251210044813_2ccb8ee7-e83d-4f7b-a150-bfb4f2ea9b0); Time taken: 41.358 seconds
INFO : OK
INFO : Concurrency mode is disabled, not creating a lock manager
+-----+
| lc.length bin | lc.record_count | percentage |
+-----+
| A. Very Short (<100 Chars) | 326 | 0.02 |
| B. Standard Abstract (100-500 Chars) | 280822 | 13.88 |
| C. Medium (501-1000 Chars) | 786033 | 38.85 |
| D. Long (>1000 Chars) | 956052 | 47.25 |
+-----+
4 rows selected (41.501 seconds)
0: jdbc:hive2://localhost:10000> 
```

Distribution of text lengths

```
VERTICES 03/03 [=====>>>] 100% ELAPSED TIME: 34.88 s
INFO : Completed executing command(queryId=hive_20251210045636_ddf796f2-087a-4251-afdb-e5c93ca7b6be); Time taken: 35.002 seconds
INFO : OK
INFO : Concurrency mode is disabled, not creating a lock manager
+-----+
| title | duplicates |
+-----+
| Hypertension in the elderly. | 15 |
| Laparoscopic cholecystectomy. | 13 |
| Malignant hyperthermia. | 12 |
| Lyme disease. | 12 |
| Neuroleptic malignant syndrome. | 11 |
+-----+
5 rows selected (35.439 seconds)
0: jdbc:hive2://localhost:10000> 
```

Top 5 Most repeated titles

```
LATERAL VIEW EXPLODE(tokens) exploded_table AS token_word
WHERE token_word NOT IN ('the', 'is', 'that', 'from', 'on', 'as', 'or', 'at', 'be', 'this')
GROUP BY token_word
ORDER BY token_count DESC
LIMIT 10
INFO : Query ID = hive_20251210044446_311cebac-0df0-4094-b726-lac7e8594de6
INFO : Total jobs = 1
INFO : Launching Job 1 out of 1
INFO : Starting task [Stage-1:MAPRED] in serial mode
INFO : Serialized to counters: [] for queryId: hive_20251210044446_311cebac-0df0-4094-b726-lac7e8594de6
INFO : Session is already open
INFO : Dag name: 311cebc
token_word,
COUNT(1) AS token_co...10 (Stage-1)
INFO : Status: Running (Executing on YARN cluster with App id application_1756163132607_32901)

+-----+
| VERTICES | MODE | STATUS | TOTAL | COMPLETED | RUNNING | PENDING | FAILED | KILLED |
+-----+
Map 1 ..... container SUCCEEDED 52 52 0 0 0 0
Reducer 2 ..... container SUCCEEDED 414 414 0 0 0 0
Reducer 3 ..... container SUCCEEDED 207 207 0 0 0 0
Reducer 4 ..... container SUCCEEDED 1 1 0 0 0 0
+-----+
VERTICES 03/03 [=====>>>] 100% ELAPSED TIME: 77.05 s
INFO : Completed executing command(queryId=hive_20251210044446_311cebac-0df0-4094-b726-lac7e8594de6); Time taken: 77.259 seconds
INFO : OK
INFO : Concurrency mode is disabled, not creating a lock manager
+-----+
| token_word | token_count |
+-----+
| of | 15325178 |
| and | 9521786 |
| in | 9090934 |
| to | 5621679 |
| is | 4937575 |
| with | 3729574 |
| was | 3428281 |
| were | 2834538 |
| by | 2505923 |
| for | 2383933 |
+-----+
10 rows selected (77.978 seconds)
```

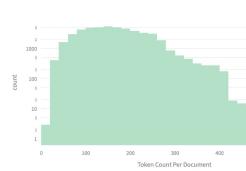
Most Common Non-stop word tokens

# Visualization - Streamlit

## Document Length Analysis

### Token Count Histogram

Distribution of Tokens Per Document (Log Scale)



### Token Count Box Plot

Statistical Summary: Quartiles and Outliers



## 3. Pipeline Transformation Flow

Comparing a small data sample (500 records) at each stage.

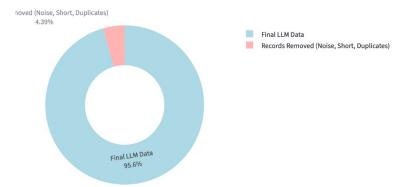
Raw Data (Input) Stage 1: Cleaned & Filtered Final Data (LLM Ready)

Cleaning removed citations, standardized content into 'main\_text', and filtered short documents. (No records removed in this step, according to the log: 2,209,839 initial vs 2,209,839 cleaned)

	id	title	main_text
0	pubmed23n0080_17157	Human-human hybridomas secreting monoclonal antibodies to the Mr 195,000 Plasmodium. Using the human lymphoblastoid cell line, GM 4672, and PBL of Gambian adults immune to	
1	pubmed23n0080_17158	A suppressor lymphokine produced by human T leukaemia cell lines. Partial characterization. Human T leukaemia cell lines spontaneously release into their medium a suppressor lymph	
2	pubmed23n0080_17159	Decay-accelerating factor is present on cultured human umbilical vein endothelial cells. Decay-accelerating factor (DAF) has been previously described only in cells of bone marrow	
3	pubmed23n0080_17160	Excitation of skinned muscle fibers by imposed ion gradients. II. Influence of quercetin and ionic gradients imposed by choline CI replacement of K methanesulfonate (MeS) at constant	
4	pubmed23n0080_17161	Ba2+-unmask K+ modulation of the Na+-K+ pump in the frog retinal pigment epithelium. This paper presents electrophysiological evidence that small changes in [K+]o modulate IP	
5	pubmed23n0080_17162	Binding of Biotin's liver and monoclonal antibodies to defined regions of human neurit. Cleavage at cysteine and chymotrypsin digestion were applied to two human neurotum	
6	pubmed23n0080_17163	Expression of myelin proteolipid protein and basic protein in normal and dysmyelinating. Expression of myelin proteins was studied in the brains of 21-day-old normal mice and thre	
7	pubmed23n0080_17164	Schwann cell marker defined by a monoclonal antibody (224-58) with species cross-react. A monoclonal antibody (mAb) designated 224-58 (IgG kappa) has been raised by fusion of	
8	pubmed23n0080_17165	Purification and characterization of a bovine cerebral cortex cell surface sialoglycopptide. A sialoglycopptide from bovine cerebral cortex cells was purified to apparent homogeni	
9	pubmed23n0080_17166	Rat and mouse monoclonal antibodies to human myelin basic protein. BALB/c mice and Lewis rats were immunized with human myelin basic protein and its N-ai	

## 4. Deduplication and Cleaning Impact Summary

### Initial Data Distribution (Total: 2,209,839)



### Pipeline Quality Assurance Report

- Total Initial Records: 2,209,839
- Total Records Removed: 96,995
- Total Data Reduction Rate: 4.39%

The removed records account for filtering out short or noisy documents (Stage 1) and removing near-duplicate documents (Stage 2: LSH). This ensures high-quality, non-redundant data for effective LLM fine-tuning.

## 2. LLM Fine-Tuning Metrics

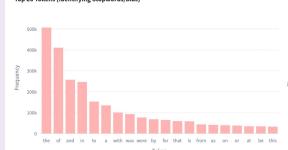
Loaded Sample Size  
50,000 records  
Mean Doc Token Count  
167 tokens

Mean Char Length  
1122 characters  
Total Data Reduction  
4.39%

### Token & Vocabulary Analysis

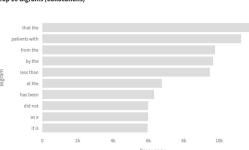
#### Top 20 Single Token Frequency

Top 20 Tokens (Identifying Stopwords/Bias)



#### Top 10 Bigrams (Collocations)

Top 10 Bigrams (Collocations)



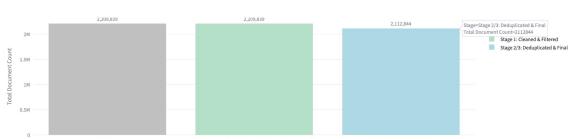
## LLM DataPrep Pipeline: Biomedical Dataset Analysis

### Showcasing Data Transformation and Quality Assurance

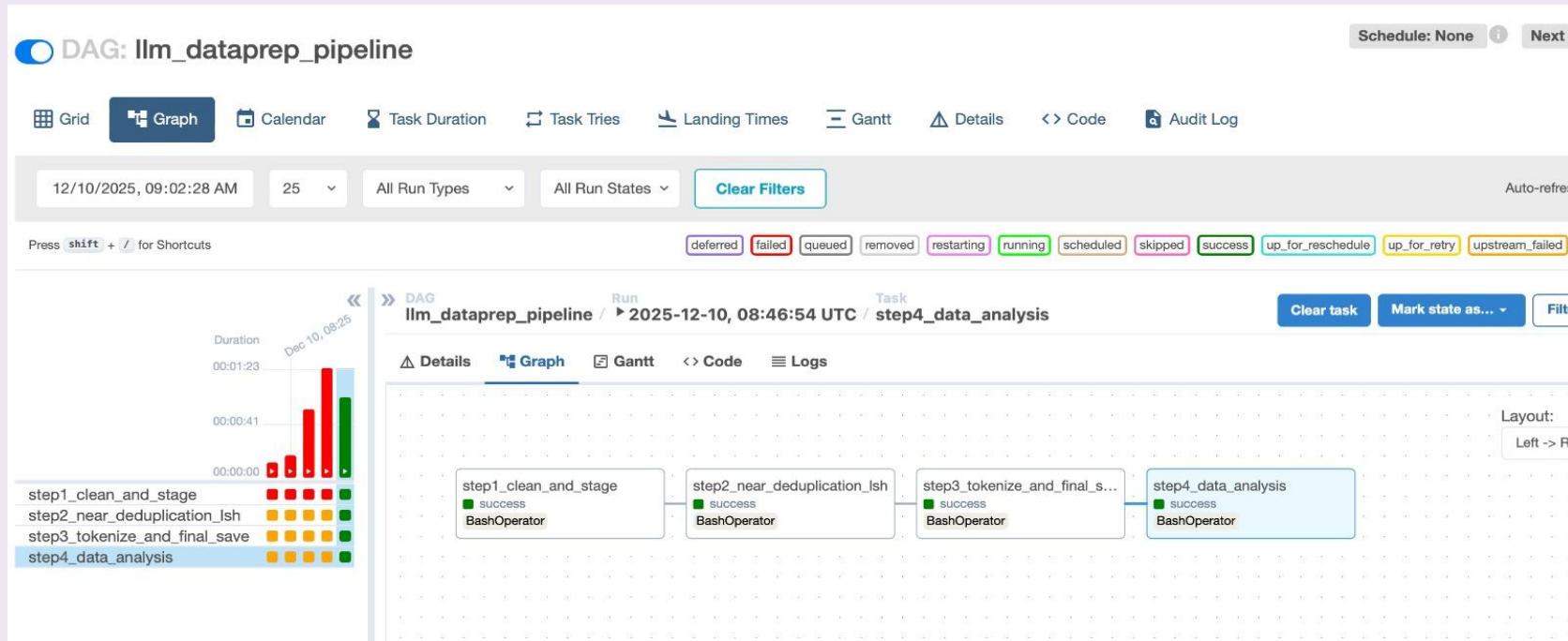
#### 1. Document Count Flow and Reduction

Tracking record count through cleaning, filtering, and deduplication (using Actual Pipeline Counts).

##### Records Flow Across Pipeline Stages



# Pipeline orchestration through Airflow



# Big Data Aspects We Focused On

- **Distributed processing:** Spark jobs across Dataproc cluster
- **Scalability:** Pipeline works on millions of biomedical records
- **Fault tolerance:** HDFS storage + Spark retry mechanisms
- **Optimized storage:** Parquet format for compression & speed
- **Parallel ETL stages:** Cleaning, dedupe, tokenization handled at scale
- **Workflow Orchestration at Scale (Airflow DAGs)** : Automated all pipeline stages using Apache Airflow, ensuring reproducibility, scheduling, and monitoring of large-scale ETL workflows.
- **Data Analysis:** Large-scale SQL analytics performed through Hive for dataset insights

## Challenges faced

- Setting up Airflow in NYU Dataproc
- Unavailability of GPU resources
- Preparing LLM fine-tuning-ready format

## Lessons Learned

- Preprocessing quality drives LLM quality
- Distributed processing is essential at this scale
- Modular ETL design reduces debugging time
- Parquet + Spark = fast and scalable

# THANK YOU

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**ANY QUESTIONS**

