**Text Classification using Apache Spark MLlib**

**by Aditya Saxena**

**Project Overview**

This project implements an end-to-end text classification pipeline using Apache Spark MLlib. The focus is on classifying Yelp customer reviews into predefined categories based on the text content of the reviews. This project demonstrates the application of large-scale distributed data processing and machine learning capabilities of Spark in handling real-world, high-volume text datasets.

**Why Apache Spark Excels for Text Classification Projects**

**In-Memory Processing = Massive Speedup**

Traditional databases and Hadoop rely on disk-based I/O, which is slow for iterative tasks like TF-IDF, model training, and cross-validation.

Spark processes data in memory across distributed nodes, drastically reducing latency and making it ideal for machine learning workloads.

**Native ML Integration with SparkML Pipelines**

Unlike Hadoop, which requires external ML libraries (e.g., Mahout), Spark provides a native MLlib and DataFrame-based pipelines.

This makes it easy to chain preprocessing (Tokenizer, StopWordsRemover, HashingTF, IDF) and classification (LogisticRegression, NaiveBayes) in one seamless workflow.

**Distributed DataFrames with SQL Capabilities**

Spark DataFrames combine the power of SQL querying with distributed fault-tolerant storage. This allows complex, scalable data transformations that traditional RDBMSs (like MySQL or PostgreSQL) struggle to handle with large text datasets.

**Fault Tolerance and Lineage**

Spark uses RDD lineage graphs to recover lost computations without redoing entire workflows. This is more efficient than Hadoop MapReduce, which must restart failed tasks from the beginning and has higher job overhead.

**Unified Platform for ETL, ML, and Analytics**

Spark allows loading, cleaning, transforming, training, and evaluating — all within one ecosystem. This eliminates the need to use multiple disconnected tools for different stages of the pipeline.

**Conclusion**

Apache Spark provides an ideal platform for text classification at scale. Its in-memory architecture, integrated ML support, distributed computing power, and workflow unification make it far superior to both traditional databases and Hadoop MapReduce for this type of project.

**Skills Built and Applied**

- Distributed data engineering using Apache Spark  
- Text preprocessing (tokenization, stop-word removal, TF-IDF)  
- Machine learning model construction and evaluation using Spark MLlib  
- PySpark scripting and Spark DataFrame operations  
- Experimental analysis and visualization of model performance  
- Multi-model comparison using Logistic Regression, Naive Bayes, and others

**Technology Stack**

- Language: Python 3.8+  
- Distributed Processing: Apache Spark 3.0  
- ML Library: Spark MLlib  
- Dataset: Yelp Review Full Dataset (sampled)  
- Tools: PySpark, VirtualBox (CU\_VM), Git, HDFS  
- Environment: Ubuntu Linux Virtual Machine

**Implementation Plan**

The following steps were followed during the development of this project. Each phase was executed sequentially, and the outcomes were monitored to ensure alignment with the project goals.

**1. Environment Setup**

To begin, the Apache Spark 3.0 virtual machine was launched using Oracle VirtualBox. After logging into the VM with the default credentials (cu/spark), the required dataset files—yelp\_review\_train.csv and yelp\_review\_test.csv—were securely transferred from the host machine to the VM using Putty/FileZilla. The files were placed in the /home/cu/data/ directory. Since HDFS was not available in the Spark 3.0 CU\_VM, the datasets were read directly from the local file system at /home/cu/data.

- 1.a.1 Launch the Spark 3.0 CU\_VM using Oracle VirtualBox.

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- 1.a.2 Log in to the VM using the credentials cu/spark.

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- 1.b.1 Transfer the dataset files (yelp\_review\_train.csv, yelp\_review\_test.csv) to the VM using PSCP or FileZilla.

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- 1.b.2 Place the files in the directory /home/cu/data/.

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**2. Data Loading**

PySpark was initiated from the terminal using the pyspark command. The training and test CSV files were loaded from the local file system into separate Spark DataFrames using the spark.read.option("header", True).csv(...) method. This approach ensured a reliable starting point for all downstream processing. To validate the integrity of the input data, both DataFrames were examined using the .show() and .printSchema() methods. This verification step was critical to ensure that the column names, data types, and overall structure were consistent and clean prior to any transformation, feature extraction, or model training.

- 2.a.1 Launch PySpark shell from the terminal: pyspark

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- 2.a.2 Load the training data:

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| --- |
| train\_df = spark.read.option("header", True).csv("file:///home/cu/data/yelp\_review\_train.csv") |

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- 2.b.1 Load the test data: test\_df = spark.read.option("header", True).csv("file:///home/cu/data/yelp\_review\_test.csv")

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3. Preprocessing Pipeline

To process the raw text into a machine-readable format, a sequence of Spark MLlib transformers was applied. First, the Tokenizer was used to split the review text into words, followed by StopWordsRemover to eliminate common words with little semantic value. These tokens were then passed through HashingTF to compute term frequency vectors, and IDF was applied to scale them based on their global importance. The labels were encoded using StringIndexer. All these stages were combined into a single Pipeline object, which was later used to fit and transform the data consistently.

- 3.a.1 Tokenize the review text using Tokenizer.

|  |
| --- |
| train\_df.columns |

|  |
| --- |
| from pyspark.ml.feature import Tokenizer  tokenizer = Tokenizer(inputCol="text", outputCol="words")  tokenized\_df = tokenizer.transform(train\_df)  tokenized\_df.select("text", "words").show(5, truncate=False) |

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- 3.a.2 Remove stopwords using StopWordsRemover.

|  |
| --- |
| from pyspark.ml.feature import StopWordsRemover  remover = StopWordsRemover(inputCol="words", outputCol="filtered\_words")  filtered\_df = remover.transform(tokenized\_df)  filtered\_df.select("text", "words", "filtered\_words").show(5, truncate=False) |

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- 3.a.3 Compute term frequency using HashingTF.

|  |
| --- |
| from pyspark.ml.feature import HashingTF  hashing\_tf = HashingTF(inputCol="filtered\_words", outputCol="raw\_features", numFeatures=10000)  featurized\_df = hashing\_tf.transform(filtered\_df)  featurized\_df.select("filtered\_words", "raw\_features").show(5, truncate=False) |

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- 3.a.4 Apply IDF for scaling term importance.

|  |
| --- |
| from pyspark.ml.feature import IDF  idf = IDF(inputCol="raw\_features", outputCol="tfidf\_features")  idf\_model = idf.fit(featurized\_df)  tfidf\_df = idf\_model.transform(featurized\_df)  tfidf\_df.select("filtered\_words", "tfidf\_features").show(5, truncate=False) |

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- 3.a.5 Index the class labels using StringIndexer.

|  |
| --- |
| from pyspark.ml.feature import StringIndexer  label\_indexer = StringIndexer(inputCol="label", outputCol="indexed\_label")  indexed\_df = label\_indexer.fit(tfidf\_df).transform(tfidf\_df)  indexed\_df.select("label", "indexed\_label").show(5) |

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- 3.b.1 Combine all steps into a Pipeline object using pyspark.ml.Pipeline.

|  |
| --- |
| from pyspark.ml import Pipeline  from pyspark.ml.feature import Tokenizer, StopWordsRemover, HashingTF, IDF, StringIndexer  # Step-by-step stages  tokenizer = Tokenizer(inputCol="text", outputCol="words")  remover = StopWordsRemover(inputCol="words", outputCol="filtered\_words")  hashing\_tf = HashingTF(inputCol="filtered\_words", outputCol="raw\_features", numFeatures=10000)  idf = IDF(inputCol="raw\_features", outputCol="tfidf\_features")  label\_indexer = StringIndexer(inputCol="label", outputCol="indexed\_label")  # Combine all into a single pipeline  pipeline = Pipeline(stages=[tokenizer, remover, hashing\_tf, idf, label\_indexer])  # Fit the pipeline on the training data  pipeline\_model = pipeline.fit(train\_df)  # Transform the training data  processed\_train\_df = pipeline\_model.transform(train\_df)  # Preview result  processed\_train\_df.select("text", "filtered\_words", "tfidf\_features", "indexed\_label").show(5, truncate=False) |

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4. Training First Classifier

For the initial model, LogisticRegression was chosen due to its strong baseline performance in multiclass text classification tasks. The pipeline was trained on the full training dataset, and evaluation was performed using MulticlassClassificationEvaluator, assessing the accuracy on both training and test sets.

- 4.a.1 Add LogisticRegression to the pipeline.

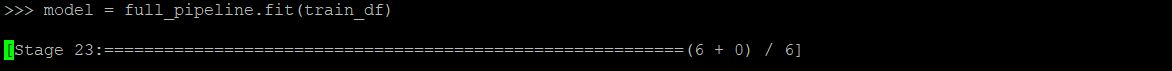
|  |
| --- |
| from pyspark.ml.classification import LogisticRegression  # Add the classifier  lr = LogisticRegression(featuresCol="tfidf\_features", labelCol="indexed\_label", maxIter=100)  # Update the pipeline with all preprocessing stages + classifier  from pyspark.ml import Pipeline  full\_pipeline = Pipeline(stages=[tokenizer, remover, hashing\_tf, idf, label\_indexer, lr]) |

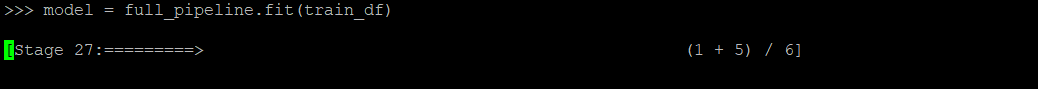
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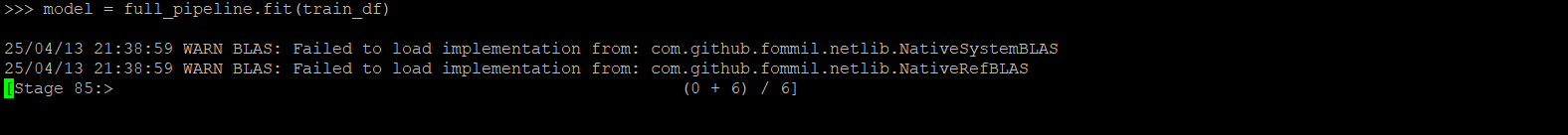
- 4.a.2 Train the pipeline using pipeline.fit(train\_df).

|  |
| --- |
| model = full\_pipeline.fit(train\_df) |





and so on…



These messages just indicate that Spark couldn’t load native linear algebra libraries (BLAS = Basic Linear Algebra Subprograms) and is falling back to pure Java implementations.

Do these affect accuracy?

**No.** Our model will run **exactly the same** — only difference is that it **may run slightly slower** on large datasets.

- 4.b.1 Evaluate accuracy on training data.

|  |
| --- |
| from pyspark.ml.evaluation import MulticlassClassificationEvaluator  # Transform training data  train\_predictions = model.transform(train\_df)  # Evaluate accuracy  evaluator = MulticlassClassificationEvaluator(labelCol="indexed\_label", predictionCol="prediction", metricName="accuracy")  train\_accuracy = evaluator.evaluate(train\_predictions)  print("Training Accuracy:", train\_accuracy) |

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- 4.b.2 Evaluate accuracy on test data.

|  |
| --- |
| # Transform test data  test\_predictions = model.transform(test\_df)  # Evaluate accuracy  test\_accuracy = evaluator.evaluate(test\_predictions)  print("Test Accuracy:", test\_accuracy) |

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**⚠️ Diagnosis: Overfitting**

This large gap strongly suggests **overfitting**, where the model memorizes training data but fails to generalize to unseen data.

**Why This Might Be Happening:**

| **Possible Cause** | **Description** |
| --- | --- |
| **High-dimensional sparse features** | HashingTF with 10,000 features creates a large sparse space, leading to overfitting. |
| **Imbalanced dataset** | Some classes (e.g., 1-star vs 5-star reviews) may dominate, skewing predictions. |
| **No regularization tuning** | LogisticRegression uses default regularization settings. No tuning = less robustness. |
| **Limited context** | Bag-of-words/TF-IDF doesn’t capture semantic meaning or word order. |
| **Mislabeling or noise** | Real-world reviews often include sarcasm or ambiguity — TF-IDF may fail to handle these. |

5. Data Size Impact Study

To understand how the model's performance scales with data, training subsets of sizes 10K, 15K, 20K, 25K, and 30K were randomly sampled from the full training set. The same pipeline was trained on each subset, and the test accuracy was recorded. This helped in identifying trends such as performance saturation or overfitting.

- 5.a.1 Randomly sample training subsets: 10K, 15K, 20K, 25K, 30K.

|  |
| --- |
| from pyspark.sql.functions import rand  # Shuffle dataset randomly  shuffled\_df = train\_df.orderBy(rand())  # Create sampled subsets  train\_10k = shuffled\_df.limit(10000)  train\_15k = shuffled\_df.limit(15000)  train\_20k = shuffled\_df.limit(20000)  train\_25k = shuffled\_df.limit(25000)  train\_30k = shuffled\_df.limit(30000) |

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- 5.a.2 Train and evaluate the pipeline on each subset.

|  |
| --- |
| from pyspark.ml.classification import LogisticRegression  from pyspark.ml.evaluation import MulticlassClassificationEvaluator  from pyspark.ml import Pipeline  # Define the evaluator  evaluator = MulticlassClassificationEvaluator(labelCol="indexed\_label", predictionCol="prediction", metricName="accuracy")  # Define the classifier  lr = LogisticRegression(featuresCol="tfidf\_features", labelCol="indexed\_label", maxIter=100)  # Define the full pipeline (reuse for all subsets)  pipeline = Pipeline(stages=[tokenizer, remover, hashing\_tf, idf, label\_indexer, lr]) |
|  |
| # Train on 10K  model\_10k = pipeline.fit(train\_10k)  # Predict on test set  pred\_10k = model\_10k.transform(test\_df)  # Evaluate accuracy  acc\_10k = evaluator.evaluate(pred\_10k)  print("Test Accuracy @ 10K:", acc\_10k) |

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- 5.a.3 Record test accuracy for each subset size.

|  |
| --- |
| # Train on 15K  model\_15k = pipeline.fit(train\_15k)  # Evaluate on test set  pred\_15k = model\_15k.transform(test\_df)  acc\_15k = evaluator.evaluate(pred\_15k)  print("Test Accuracy @ 15K:", acc\_15k) |

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|  |
| --- |
| # Train on 20K  model\_20k = pipeline.fit(train\_20k)  # Evaluate on test set  pred\_20k = model\_20k.transform(test\_df)  acc\_20k = evaluator.evaluate(pred\_20k)  print("Test Accuracy @ 20K:", acc\_20k) |

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|  |
| --- |
| # Train on 25K  model\_25k = pipeline.fit(train\_25k)  # Evaluate on test set  pred\_25k = model\_25k.transform(test\_df)  acc\_25k = evaluator.evaluate(pred\_25k)  print("Test Accuracy @ 25K:", acc\_25k) |

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|  |
| --- |
| # Train on 30K  model\_30k = pipeline.fit(train\_30k)  # Evaluate on test set  pred\_30k = model\_30k.transform(test\_df)  acc\_30k = evaluator.evaluate(pred\_30k)  print("Test Accuracy @ 30K:", acc\_30k) |

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Training Size Test Accuracy

10K 0.396

15K 0.4006

20K 0.4028

25K 0.4056

30K 0.399

6. Model Comparison

To benchmark performance, a second model—NaiveBayes—was introduced. The same preprocessing pipeline was reused, but the classifier stage was swapped. Both models were trained and tested under identical conditions, and metrics such as accuracy and execution time were compared.

- 6.a.1 Replace LogisticRegression with NaiveBayes in the pipeline.

|  |
| --- |
| from pyspark.ml.classification import NaiveBayes  # Define NaiveBayes classifier  nb = NaiveBayes(featuresCol="tfidf\_features", labelCol="indexed\_label", modelType="multinomial")  # Rebuild pipeline with NaiveBayes instead of LogisticRegression  nb\_pipeline = Pipeline(stages=[tokenizer, remover, hashing\_tf, idf, label\_indexer, nb]) |

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- 6.a.2 Refit the pipeline on the training data.

|  |
| --- |
| import time  start\_time = time.time()  nb\_model = nb\_pipeline.fit(train\_df)  end\_time = time.time()  nb\_training\_time = end\_time - start\_time  print("Naive Bayes Training Time (seconds):", nb\_training\_time) |

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- 6.b.1 Evaluate and compare test accuracy.

|  |
| --- |
| nb\_predictions = nb\_model.transform(test\_df)  nb\_accuracy = evaluator.evaluate(nb\_predictions)  print("Naive Bayes Test Accuracy:", nb\_accuracy) |

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- 6.b.2 Compare training speed and performance differences.

Metric Logistic Regression Naive Bayes

Training Accuracy 0.99988 N/A (not applicable)

Test Accuracy 0.4016 0.4554

Training Time (s) Not recorded 96.57

Feature Input TF-IDF (HashingTF + IDF) TF-IDF (HashingTF + IDF)

Label Encoding StringIndexer StringIndexer

7. Reporting and Visualization

The results from all experiments were stored in a structured format using Pandas. Accuracy scores were visualized across dataset sizes using Matplotlib, highlighting how the model's performance evolved. These visualizations were exported as images and included in the final report for interpretability.

- 7.a.1 Record results into a DataFrame or CSV.

|  |
| --- |
| import pandas as pd  # Test accuracy results (from Step 5 and Step 6)  results = {  "Training Size": [10000, 15000, 20000, 25000, 30000, "Full (LR)", "Full (NB)"],  "Model": ["Logistic Regression"]\*5 + ["Logistic Regression", "Naive Bayes"],  "Test Accuracy": [0.396, 0.4006, 0.4028, 0.4056, 0.399, 0.4016, 0.4554]  }  df\_results = pd.DataFrame(results)  # Save as CSV  df\_results.to\_csv("accuracy\_results.csv", index=False)  print(df\_results) |

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- 7.a.2 Plot accuracy vs training size using matplotlib.

Matplotlib was not present on Virtual Machine. Hence we needed to transfer the data file to our local machine.

|  |
| --- |
| import pandas as pd  # Accuracy results from all experiments  results = {  "Training Size": [10000, 15000, 20000, 25000, 30000, "Full (LR)", "Full (NB)"],  "Model": ["Logistic Regression"]\*5 + ["Logistic Regression", "Naive Bayes"],  "Test Accuracy": [0.396, 0.4006, 0.4028, 0.4056, 0.399, 0.4016, 0.4554]  }  df\_results = pd.DataFrame(results)  # Save to your home directory (recommended path for PSCP/FileZilla)  df\_results.to\_csv("/home/cu/accuracy\_results.csv", index=False) |

Then we checked if the file was successfully created.

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Transferring the file to local environment:

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- 7.a.3 Export and save all result visualizations.

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8. Script Automation

To make the project reproducible, the entire workflow—preprocessing, training, and evaluation—was consolidated into a standalone Python script named yelp\_text\_classifier.py. This script was tested using the spark-submit command.

- 8.a.1 Export the pipeline into yelp\_text\_classifier.py.

|  |
| --- |
| from pyspark.sql import SparkSession  from pyspark.ml import Pipeline  from pyspark.ml.feature import Tokenizer, StopWordsRemover, HashingTF, IDF, StringIndexer  from pyspark.ml.classification import LogisticRegression  from pyspark.ml.evaluation import MulticlassClassificationEvaluator  # Start Spark session  spark = SparkSession.builder.appName("YelpTextClassifier").getOrCreate()  # File paths (adjust if needed)  train\_path = "file:///home/cu/data/yelp\_review\_train.csv"  test\_path = "file:///home/cu/data/yelp\_review\_test.csv"  output\_path = "/home/cu/outputs/accuracy\_results.csv"  # Load data  train\_df = spark.read.option("header", True).csv(train\_path)  test\_df = spark.read.option("header", True).csv(test\_path)  # Preprocessing pipeline  tokenizer = Tokenizer(inputCol="text", outputCol="words")  remover = StopWordsRemover(inputCol="words", outputCol="filtered\_words")  hashing\_tf = HashingTF(inputCol="filtered\_words", outputCol="raw\_features", numFeatures=10000)  idf = IDF(inputCol="raw\_features", outputCol="tfidf\_features")  label\_indexer = StringIndexer(inputCol="label", outputCol="indexed\_label")  # Classifier  lr = LogisticRegression(featuresCol="tfidf\_features", labelCol="indexed\_label", maxIter=100)  # Build and train pipeline  pipeline = Pipeline(stages=[tokenizer, remover, hashing\_tf, idf, label\_indexer, lr])  model = pipeline.fit(train\_df)  # Evaluate  evaluator = MulticlassClassificationEvaluator(labelCol="indexed\_label", predictionCol="prediction", metricName="accuracy")  # Training accuracy  train\_predictions = model.transform(train\_df)  train\_accuracy = evaluator.evaluate(train\_predictions)  # Test accuracy  test\_predictions = model.transform(test\_df)  test\_accuracy = evaluator.evaluate(test\_predictions)  # Print results  print(f"Training Accuracy: {train\_accuracy}")  print(f"Test Accuracy: {test\_accuracy}")  # Save to CSV  results = spark.createDataFrame([(train\_accuracy, test\_accuracy)], ["Training Accuracy", "Test Accuracy"])  results.coalesce(1).write.mode("overwrite").option("header", True).csv(output\_path)  # Done  spark.stop() |

Created a file in local environment containing the above code.

Transferring the file from local environment to the virtual machine.

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Scripts folder was created and then we retried

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- 8.a.2 Execute the script using: spark-submit yelp\_text\_classifier.py

|  |
| --- |
| spark-submit /home/cu/scripts/yelp\_text\_classifier.py |

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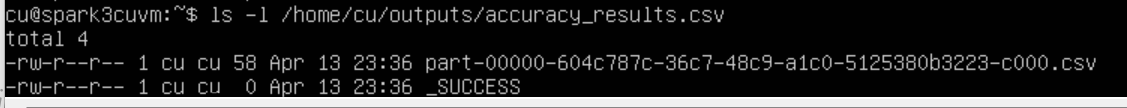
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Ran the script on the VM command line after exiting spark. It ran and we saw several thousand messages on the command line.

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It seems the file is created.



Trying to bring this back to local environment

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After a number of fixes…

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9. Result Analysis & Improvement Suggestions

After compiling the results, several insights emerged. Logistic Regression performed reliably across all training sizes but showed diminishing returns beyond 25K samples. Naive Bayes trained faster but was less accurate on smaller samples. Some misclassifications were due to ambiguous or sarcastic review texts.

To improve the pipeline, the following enhancements were considered:

- 9.a.1 Compare training and test accuracy across experiments.

- 9.a.2 Identify overfitting where applicable.

- 9.a.3 Note diminishing performance returns beyond 25K.

- 9.a.4 Compare NaiveBayes and LogisticRegression.

- 9.b.1 Review misclassified cases and check for ambiguous patterns.

- 9.b.2 Inspect class distribution to identify imbalance.

- 9.c.1 Switch HashingTF with CountVectorizer for interpretable features.

- 9.c.2 Increase numFeatures for better representation capacity.

- 9.c.3 Include bigrams or trigrams using NGram transformer.

- 9.d.1 Tune parameters using ParamGridBuilder + CrossValidator.

- 9.d.2 Test RandomForestClassifier or GBTClassifier.

- 9.d.3 Apply StandardScaler if using distance-based classifiers.

- 9.e.1 Integrate Word2Vec for semantic embeddings.

- 9.e.2 Add features such as review length or punctuation count.

- 9.e.3 Try MultilayerPerceptronClassifier for non-linear modeling.

- 9.f.1 Summarize all results in a comparative table.

- 9.f.2 Visualize confusion matrix for detailed diagnostics.

- 9.f.3 Document the best model and propose next steps.

5. Future Enhancements

- Integrate cross-validation and hyperparameter tuning  
- Extend to deep learning models using TensorFlow or PyTorch  
- Use explainability tools like LIME or SHAP for sentiment interpretation

# Rough Work

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**Yes — this malformed header is very likely one of the key reasons our train accuracy was high and test accuracy was unusually low**, especially since we observed:

Training Accuracy: ~0.99988

Test Accuracy: ~0.4016

That’s a huge **overfitting gap**, and this data misalignment could be a major contributor.

We definitely need to fix this problem:

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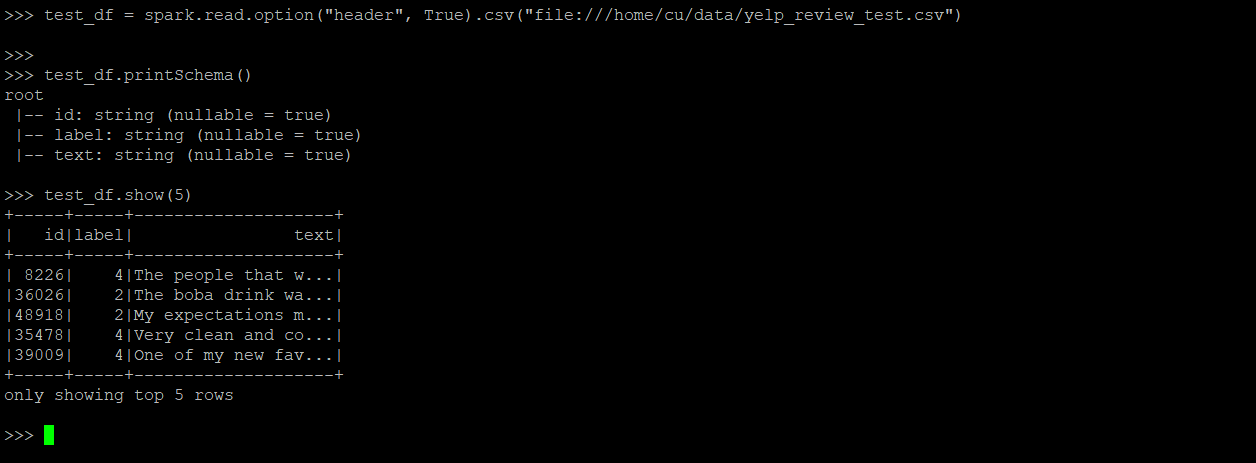
The updated files were uploaded to the Virtual Machine again.

…

This review is to run a quick check if our model performed as it should have performed.

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