Cloud Computing - Project Report

Cloud-Busters

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https://github.com/lorenzo-vezzani/inverted-index-and-search

1 Introduction

Our project for the Cloud Computing course involves developing a basic search engine backend through the construction of an **Inverted Index**, a fundamental data structure in information retrieval systems such as **Google Search**. The main goal is to process a collection of text files and efficiently map each word to the files in which it appears, along with the frequency of its occurrences. Subsequently we had to analyze and compare the performance of a Java-based application using the **Hadoop** framework with that of a Python-based application using the **Spark** framework. Finally we have to build a **search query** in Python based on the inverted indexes produced.

We tried to make the code as optimized as possible by doing a lot of tests to try to optimize the execution time and memory usage.

2 Equipment

The tests were conducted on three identical virtual machines, each configured with the following hardware and software specifications:

- **CPU**: 2 virtual CPUs (vCPUs), mapped to Intel(R) Xeon(R) Silver 4208 CPU @2.10GHz, provided via KVM virtualization
- **RAM**: 6.8 GB of system memory
- **Disk**: 39 GB of allocated virtual storage (ext4 filesystem)
- **Operating System**: Ubuntu 22.04.1 LTS (Jammy Jellyfish), 64-bit

3 Dataset

We selected a 1583.5 MB corpus of 2685 plain-text files from Project Gutenberg, covering diverse fields including philosophy, science, theology, psychology, literature and other cultural subjects, to stress and tests our indexer across a broad range of real-world texts. This variety tests the system against typical literary content as well as challenging patterns, mirroring real-world search engine demands on both natural language and specialized data. File sizes vary from 5 KB to 250 MB: most are under 1 MB (reflecting typical book chapters or short essays), 329 fall between 1 MB and 7 MB (full-length books) and one extreme outlier ("Human_Genome_Project-Chromosome_1.txt", 250 MB) contains raw nucleotide sequences. Including this genomic text deliberately exposes our inverted-index builder to vast, mostly unique tokens—mimicking workloads with high vocabulary cardinality and ensuring our system handles both common-word skew and near-unique string distributions. By including files ranging from kilobytes to megabytes, the dataset enables a rigorous evaluation of how indexing and search-query systems scale with input size.

4 MapReduce and Hadoop code

The system uses **MapReduce**, via the **Hadoop** framework, to process large-scale data efficiently. The Hadoop cluster is optimized for virtual machines with limited memory through customized YARN and MapReduce settings. YARN manages resources and memory (up to 5 GB per node), while MapReduce configurations allocate 2048 MB to key tasks, with JVM heaps limited ot 1536 MB.

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5 Spark code

The Spark-related Python code was implemented based on the functional patterns and structure demonstrated during the lectures. **Apache Spark** is an open-source, distributed data processing engine designed for fast in-memory analytics and large-scale workload orchestration. Spark doesn't strictly use **MapReduce**, but it supports map and reduce operations but runs them within a more flexible **DAG** execution model rather than the rigid two-stage MapReduce paradigm.

RDD_inverted_index_search.py was the first version of the **Spark** code. Its **build_index** method begins by reading one or more text files from **HDFS** into Spark as an **RDD** of (filepath, content) pairs using **wholeTextFiles**, then unites these RDDs into a single **collection**. It applies a **flatMap** transformation that lowercases and **tokenizes** each document via a regular expression, counts word occurrences locally with Python's Counter, and emits tuples of the form (word, filename: count). By performing **local counting** before the **shuffle**, the method minimizes network traffic. Next, it aggregates all partial maps for each word across partitions using **aggregateByKey**, merging dictionaries of filename counts into a complete postings list. The resulting RDD of (word, postingsDict) is converted into tab-delimited strings like:

”word f̂ile1:count1 f̂ile2:count2”

Finally, it writes the index either as plain text via saveAsTextFile or as structured JSON or Parquet through a Spark DataFrame, producing an efficient, fully distributed inverted index.

Spark configuration sets the cluster manager to YARN and enables event logging, storing logs in HDFS. It activates the history server with logs updated every 10 seconds and accessible via port 18080. Executor resources are set to 2 cores and 3 GB of memory, while the driver is allocated 1 GB of memory plus 1536 MB of overhead.

However this code had poor performance, performance that we expected better from Spark. So we build another version. Spark's **DataFrames** wrap RDDs with a schema and declarative API, letting Spark Catalyst optimizer and Tungsten execution engine apply column-level and query-plan optimizations for far better performance and memory use than raw RDDs.

In the new **inverted_index_search.py**, it first loads each specified path into a unified DataFrame annotated with a filename column, gracefully skipping any unreadable files. It then applies a sequence of Spark SQL transformations: all non-alphanumeric characters are stripped via **regexp_replace**, text is lowercased and split on whitespace and each word is exploded into its own row. Empty tokens are filtered out to ensure data quality. So we have a more optimized **tokenization**. In the next phase, the code groups by word and filename to compute per-document term frequencies, then concatenates these as filename:count strings. A second grouping by word collects and sorts the full postings list into an array, producing one row per unique term with its complete, ordered document list. Finally the output is either written as plain text (with words and tab-separated postings) JSON, or Parquet. This approach leverages Spark's built-in DataFrame optimizations and avoids manual RDD manipulations while delivering a scalable inverted index.

This code works better with lower Spark configurations. Executor resources are set to 2 cores and 2 GB of memory, while the driver is allocated 1 GB of memory plus 512 MB of overhead.

6 Non-parallel code

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7 Test and Results

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