# Designing a metadata framework for bigdata models in Cloudera Data Lakes across AWS, Azure, and GCP

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***Abstract*— This research presents an innovative metadata framework design for big data models in Cloudera Data Lakes across AWS, Azure, and GCP cloud platforms. The study focuses on migrating metadata using Data Vault data models, utilizing PySpark and SparkSQL for analysis.**

**As big data environments grow in complexity, accurate metadata migration becomes crucial. This study explores best practices and automation tools for efficient metadata migration in large-scale environments.**

**The research evaluates unique features of AWS, Azure, and GCP, including data storage, processing, security, and cost-effectiveness. It also assesses scalability and usability for managing big data in Cloudera Data Lakes with Data Vault data models.**

**Findings show that AWS offers extensive services and tools, while Azure and GCP provide cost-effective options. AWS benefits from a large partner and developer network, aiding in managing big data in Cloudera Data Lakes with Data Vault models.**

**This study provides innovative insights into metadata framework design and the capabilities of AWS, Azure, and GCP for big data management in Cloudera Data Lakes, aiding organizations in selecting the appropriate cloud platform.**

***Index Terms*—Cloud Platforms AWS Azure GCP , Big Data Environments, Cloudera, Metadata Migration, PySpark, SparkSQL**

## I. INTRODUCTION

In recent years, the exponential growth of data generated by organizations has posed significant challenges in managing and storing such vast volumes of information. To tackle these challenges, [1] cloud-based solutions have gained increasing popularity. Amazon Web Services (AWS), Microsoft Azure, and Google Cloud Platform (GCP) are prominent cloud service providers offering solutions for managing and processing big data.[2]

Cloudera Data Lakes have emerged as one of the most popular big data management solutions, adopted by numerous organizations for their data storage and analysis needs. However, migrating metadata from Cloudera Data Lakes can be a complex process. Utilizing Data Vault data models can simplify this migration process, providing a more efficient solution.[3]

This paper aims to provide a comparative analysis of AWS, Azure, and GCP, the three leading cloud service providers, for migrating metadata of big data in Cloudera Data Lakes using Data Vault data models. The analysis will consider crucial factors such as cost, ease of use, scalability, security, and performance. The goal is to provide a comprehensive comparison that assists organizations in making informed decisions when choosing a cloud platform for their big data needs.[4]

Metadata migration plays a critical role in ensuring the accuracy and completeness of transferred data within any big data environment. [5] Automation tools greatly streamline this process, but it is essential to follow best practices to ensure the quality, governance, and security of the migrated data. This review examines the best practices for metadata migration in big data environments using automation tools, with a

particular focus on data quality, data governance, and data security considerations.[6]

The key contributions of this research paper include:
In-depth analysis of AWS, Azure, and GCP capabilities for managing big data workloads, particularly within Cloudera Data Lakes and Data Vault data models.
Comparison of automation tools and frameworks available for each cloud platform, evaluating features, ease of use, and suitability for specific use cases.
Review of best practices for migrating metadata in big data environments using automation tools, including considerations for data quality, data governance, and data security.
Study of the PySpark framework and its capabilities for processing large datasets, including optimization techniques for performance and scalability.
Evaluation of trade-offs between different storage and compute options available on each cloud platform, including object storage, block storage, and compute instances.
Comparison of pricing models and cost structures among AWS, Azure, and GCP, highlighting strategies for optimizing costs in big data workloads.
Discussion of challenges and opportunities associated with integrating multiple cloud platforms into a unified big data ecosystem, addressing data integration, movement, and synchronization across diverse cloud environments.
PySpark, a powerful open-source data processing framework, provides a Python interface to Apache Spark, a distributed computing system designed for processing large-scale datasets. PySpark is widely used for big data processing due to its ability to handle large datasets efficiently by distributing the workload across multiple nodes in a cluster. This parallel processing capability significantly reduces the time required for data processing tasks.[7]
In the context of this research, PySpark can be leveraged to reduce the number of job columns from 4200 to equal amounts of 330 job master and aggregated metadata.csv files. This achievement is made possible by harnessing PySpark's data processing capabilities, including filtering, aggregating, and transforming data.[8]
To implement this solution, AWS Glue, Azure Data Factory, or GCP Dataproc can be utilized for workflow orchestration. These cloud services provide a platform for running PySpark jobs at scale and managing the execution of PySpark workflows.[9]
Potential use cases for customers benefiting from this solution include:
Financial institutions processing large volumes of transactional data for fraud detection and risk management.
Retail companies analyzing customer purchase patterns to optimize pricing and marketing strategies.
Healthcare organizations processing patient data for clinical research and drug discovery.
Manufacturing companies

## II. PYSPARK FOR METADATA AGGREGATION

Best Practices for Metadata Migration in Big Data Environments:
The given code is using PySpark to merge three data frames (DF1, DF2, and DF3) and select specific columns based on the job_name column present in DF1 and join it with the job_name column present in the job master data frame. The merged data is then used to create aggregated metadata. Here is a brief explanation of the code:[10]
The code imports required PySpark libraries such as SparkSession, SparkConf, functions, col, and lit. It also imports the pandas and re libraries. Then, it sets the Spark log level to "ERROR" to minimize log messages.
The code reads three CSV files (job_master_data.csv, jobs_column_list.csv, and linked_job_name_data.csv) using the spark.read.format() method and loads them into three PySpark data frames (df1, df2, and df3) using option("header", "true") to indicate that the first row of the CSV file contains the column names.
The data frames are then registered as temporary tables using the createOrReplaceTempView() method.
The code defines a list c containing all the column names that need to be selected from the merged data frame. The data frames are then aliased as a, b, and c.
The join() method is used to join the three data frames on the job_name column. df1 is joined with df2 on job_name column using a left join, and df2 is joined with df3 on job_name column using a left join. The resulting data frame contains all columns from df1, b, and c. The select() method is used to select the required columns specified in the c list from the merged data frame. The resulting data frame is then sorted in ascending order based on the job_name

column. Finally, the resulting data frame is collected and stored in separate variables based on their respective column names using collect() method and multiple v variables (e.g., v0, v1, etc.).

Overall, the given code uses PySpark to merge three data frames and select specific columns based on job_name column present in DF1 and join it with the job_name column present in the job master data frame. The merged data is then used to create aggregated metadata.

Understand the source and destination environments: Before beginning a metadata migration, it is essential to thoroughly understand both the source and destination environments. This includes identifying the type and format of the metadata being migrated, the systems and applications involved, and any dependencies or constraints that may impact the migration process.

This Python code reads three CSV files as PySpark DataFrames, joins them, and selects certain columns. Here is a brief description of the steps:

The CSV files are read as PySpark DataFrames: df1 from file df1_job_master_lst, df2 from file df2_job_column_lst, and df3 from file df3_job_linked_lst. The delimiter used is, and the header row is considered in all three cases.

The three DataFrames are registered as temporary views with the names d1, d2, and d3.

The columns to select are defined in a list named c.

Aliases are created for the three DataFrames: a for df1, b for df2, and c for df3.

The DataFrames are joined in the following order: df1 and df2 on the condition that a.job_name = b.job_name, and df2 and df3 on the condition that b.job_name = c.job_name. The join type is left, so all rows from df1 are included in the result.

The resulting DataFrame is selected by column names from both the df2 and df3 DataFrames.

The resulting DataFrame is sorted by the job_name column in ascending order.

The resulting DataFrame is not returned or saved, but its content can be collected to a local variable, which seems to be the purpose of the following lines of code that initialize a large number of empty lists (v0 to v45). These lists are likely used to store the selected columns from the DataFrame.

These are import statements used in Python code for working with Apache Spark's Structured APIs, specifically the PySpark library for Python. Here's a brief explanation of each line:

from pyspark.sql import SparkSession: This line imports the SparkSession class from the pyspark.sql module. A SparkSession is the entry point to Spark functionality and allows you to create DataFrames, register DataFrames as tables, execute SQL queries, and more.

from pyspark.conf import SparkConf: This line imports the SparkConf class from the pyspark.conf module. SparkConf is a configuration object that sets various Spark parameters.

from pyspark.sql import functions as F: This line imports the functions module from the pyspark.sql package and renames it as F. The functions module contains a wide range of built-in functions that can be applied to columns in a Spark DataFrame.

from pyspark.sql.functions import col: This line imports the col function from the pyspark.sql.functions module. col is a function that returns a column from a DataFrame based on the column name.

from pyspark.sql.functions import lit: This line imports the lit function from the pyspark.sql.functions module. lit is a function that creates a literal value that can be used as a column in a DataFrame.[11]

## III. BIG DATA ANALYSIS IN CLOUD PLATFORMS

Comparing AWS, Azure, and GCP cloud platforms for the migration of metadata of big data in Cloudera Data Lake in Data Vault Data Models can be done by evaluating their features, capabilities, and pricing.

AWS, Azure, and GCP all offer services for big data storage and processing, but each platform has its strengths and weaknesses. For example, AWS has a strong presence in the big data market with services such as Amazon S3, Redshift, and EMR. Azure has also made significant investments in big data services with offerings such as Azure Data Lake Storage and Azure HDInsight. GCP, on the other hand, has a strong focus on machine learning and analytics with services like BigQuery and Dataflow.[12]

When it comes to migrating metadata in Cloudera Data Lake, each platform has its own approach. AWS [13] has a service called AWS Glue that allows you to automate the discovery, cataloging, and migration of data. Azure offers Azure Data Factory and Azure

Databricks for data integration and transformation. GCP offers Cloud Data Fusion for data integration and Cloud Dataproc for data processing.

In terms of pricing, all three platforms offer a pay-as-you-go model, but the specific costs vary based on usage and the services used. It's important to consider the total cost of ownership when evaluating cloud platforms for big data migration.

Overall, it's important to consider the specific requirements and goals of your big data migration project when evaluating cloud platforms. Each platform has its strengths and weaknesses, and the best choice will depend on your unique needs. [15]

## IV. BIG DATA CAPABILITIES IN CLOUD PLATFORM

Develop a migration plan: A well-defined migration plan is critical for ensuring the successful transfer of metadata. This plan should include a detailed timeline, clear objectives, and a comprehensive list of tasks to be completed. It should also identify any potential risks or challenges that may arise during the migration process and include contingency plans to address them.

### *4.1 AWS offerings for Cloudera big data*

Amazon Web Services (AWS) offers a broad range of services for managing big data workloads, including those in the context of Cloudera Data Lakes and Data Vault data models.

AWS offers Amazon EMR (Elastic MapReduce), a fully-managed service that makes it easy to process vast amounts of data using Apache Hadoop and Spark. Amazon EMR supports many Hadoop ecosystem tools and frameworks, including Pig, Hive, HBase, Flink, and Presto. It also integrates with Amazon S3 (Simple Storage Service) and other AWS services for data storage, processing, and analysis.

For managing data in Cloudera Data Lakes, AWS offers Amazon S3, which provides highly scalable, durable, and secure object storage for data lakes. AWS also offers Amazon Redshift, a fully-managed data warehouse service that makes it easy to analyze data using standard SQL and business intelligence (BI) tools.

For data modeling, AWS offers Amazon Athena, a serverless interactive query service that makes it easy to analyze data in Amazon S3 using standard SQL. AWS also offers AWS Glue, a fully-managed ETL (Extract, Transform, and Load) service that makes it easy to prepare and load data for analytics.

For security, AWS offers a broad range of services, including AWS Identity and Access Management (IAM), AWS Key Management Service (KMS), AWS CloudTrail, and AWS Config. These services help customers to control access to their data, encrypt data at rest and in transit, monitor and audit activity, and comply with regulations and standards.

Overall, AWS provides a comprehensive set of services and tools for managing big data workloads, including those in the context of Cloudera Data Lakes and Data Vault data models. AWS's services are highly scalable, flexible, and secure, and integrate well with other AWS services and tools.[16,17,18,19,20,21]

### *4.2. Azure offerings for Cloudera big data*

Azure provides several services for managing big data workloads in the context of Cloudera Data Lakes and Data Vault data models. Some of the key capabilities are:

Azure HDInsight: This is a fully-managed cloud service that makes it easy to process big data using popular open-source frameworks such as Hadoop, Spark, and Hive. It integrates with Cloudera Data Lakes and provides built-in connectors to Azure Data Lake Storage and other Azure services.

Azure Data Lake Storage: This is a scalable and secure data lake solution that can store and analyze large volumes of data from different sources. It integrates with HDInsight and provides high-performance access to data using Hadoop Distributed File System (HDFS) and Blob Storage APIs.

Azure Synapse Analytics: This is a cloud-based analytics service that combines big data and data warehousing to provide a unified experience for data integration, exploration, and analytics. It integrates with HDInsight and provides built-in connectors to Azure Data Lake Storage and other Azure services.

Azure Databricks: This is a collaborative, cloud-based platform for data engineering, data science, and machine learning. It provides a unified experience for working with big data using Spark and other popular open-source frameworks. It integrates with Azure services such as HDInsight, Data Lake Storage, and Synapse Analytics.

Azure Stream Analytics: This is a real-time data streaming service that can process millions of events per second from different sources. It integrates with HDInsight and provides built-in connectors to Azure Event Hubs, IoT Hub, and other Azure services.
Overall, Azure provides a comprehensive set of services for managing big data workloads in the context of Cloudera Data Lakes and Data Vault data models. These services are designed to be scalable, secure, and cost-effective, and can help organizations derive valuable insights from their big data.[22]

### *4.3 GCP offerings for Cloudera big data*

Google Cloud Platform (GCP) offers various services and tools for managing big data workloads in the context of Cloudera Data Lakes and Data Vault data models. Some of these capabilities include:
Storage and Data Management: GCP provides multiple storage options for big data, such as Cloud Storage, Cloud Bigtable, and Cloud Spanner. Cloud Storage is an object storage service that offers unlimited storage capacity and allows for efficient data management. Cloud Bigtable is a NoSQL database service that can handle large amounts of data with low latency, while Cloud Spanner is a globally distributed relational database that provides strong consistency and horizontal scaling.
Data Processing: GCP provides various tools for processing big data, such as Dataflow, Dataproc, and BigQuery. Dataflow is a managed service for building data pipelines that can handle both batch and stream processing. Dataproc is a managed service for running Apache Hadoop and Spark jobs on a cluster, while BigQuery is a fully managed, serverless data warehouse that allows for high-performance querying and analysis of large datasets.

Security: GCP offers various security features to protect big data workloads, such as Identity and Access Management (IAM), Cloud Key Management Service (KMS), and Cloud Data Loss Prevention (DLP). IAM allows for fine-grained access control of GCP resources, while KMS provides centralized key management and cryptographic operations. Cloud DLP helps to detect and protect sensitive data in big data workloads.

Cost-Effectiveness: GCP offers various cost-effective options for managing big data workloads, such as pre-emptible VMs, committed use discounts, and sustained use discounts. Pre-emptible VMs are short-lived instances that can be used for batch processing at a lower cost, while committed use discounts offer savings for sustained usage of VMs. Sustained use discounts provide automatic discounts based on the amount of usage of certain GCP services over time.
Overall, GCP provides a comprehensive set of services and tools for managing big data workloads in the context of Cloudera Data Lakes and Data Vault data models.[23]

## V. BIG DATA TOOLS AND FRAMEWORKS

Ensure data quality: Ensuring the quality of the migrated metadata is essential to maintaining data accuracy and completeness. This includes verifying the consistency and validity of the data, as well as identifying and addressing any errors or discrepancies. Automated data profiling and validation tools can help ensure data quality and accuracy.
Establish data governance: Effective data governance is critical to ensuring the security, privacy, and compliance of the migrated data. This includes implementing policies and procedures to manage data access, usage, and retention, as well as establishing clear roles and responsibilities for data management and oversight.
Implement data security measures: Protecting the security of the migrated data is essential to preventing unauthorized access, data breaches, and other security threats. This includes implementing data encryption, access controls, and other security measures to ensure the confidentiality and integrity of the data.

### *5.1 AWS big data tool and framework*

The advent of big data has led to a proliferation of tools and frameworks for processing and analyzing large datasets. AWS offers a variety of tools and services for managing big data workloads, and there are also numerous open-source and third-party tools available that can be used in conjunction with AWS. In this paper, we will provide a comparison of various automation tools and frameworks available for AWS, focusing on their features, ease of use, and suitability for specific use cases.

#### 5.1.1 AWS Native Tools and Services

AWS Glue:

Overview: AWS Glue is a fully managed extract, transform, and load (ETL) service that makes it easy to prepare and load data for analytics. It provides automated discovery, cataloging, and transformation of data, allowing users to create and run ETL jobs at scale.
Features: Key features of AWS Glue include data cataloging, job authoring, job execution, data transformation, and integration with various data sources and destinations.

Use Cases: AWS Glue is commonly used for data preparation and ETL processes in data lakes, data warehousing, log analysis, data migration, and data integration scenarios.

Amazon EMR:
Overview: Amazon Elastic MapReduce (EMR) is a cloud-based big data platform that simplifies the processing and analysis of large datasets. It provides a managed Hadoop framework along with other popular distributed computing frameworks like Spark, HBase, and Presto.

Features: Amazon EMR offers features such as automatic scaling, flexible data storage options, data encryption, monitoring and management tools, and integration with various data sources and analytics tools.

Use Cases: Amazon EMR is used for a wide range of big data use cases, including log analysis, data warehousing, machine learning, real-time analytics, and processing large-scale data pipelines.

Amazon Redshift:
Overview: Amazon Redshift is a fully managed data warehousing service designed for analyzing large datasets. It provides high-performance, columnar storage, and parallel query execution to deliver fast query performance on large-scale data.

Features: Key features of Amazon Redshift include columnar storage, automatic compression, parallel query execution, data ingestion options, security and encryption, and integration with popular business intelligence tools.

Use Cases: Amazon Redshift is commonly used for business intelligence and data analytics applications, including reporting and dashboards, ad-hoc queries, data exploration, and complex analytics tasks on large datasets.

5.1.2 Third-Party Tools and Frameworks
Apache Hadoop:
Overview: Apache Hadoop is an open-source framework for distributed processing and storage of large datasets across clusters of computers. It provides a scalable and fault-tolerant solution for processing and analyzing big data.
Features: Hadoop consists of two core components - the Hadoop Distributed File System (HDFS) for storing data across multiple machines, and the MapReduce programming model for distributed processing. It also includes various ecosystem projects like YARN, Hive, Pig, and HBase for additional functionalities.
Use Cases: Apache Hadoop is used for a wide range of use cases, including data warehousing, log processing, recommendation systems, fraud detection, sentiment analysis, and large-scale data processing in various industries.
Apache Spark:
Overview: Apache Spark is an open-source, distributed computing system designed for processing and analyzing large-scale datasets. It provides an in-memory computing engine that enables faster data processing and supports a wide range of data processing tasks.
Features: Spark offers a unified framework for batch processing, interactive queries, streaming data, and machine learning. It provides APIs in multiple programming languages, including Scala, Java, Python, and R, and supports various data sources and machine learning libraries.
Use Cases: Apache Spark is used in diverse use cases, such as real-time analytics, machine learning, graph processing, ETL (Extract, Transform, Load) pipelines, fraud detection, log analysis, and recommendation systems.
Apache Kafka:
Overview: Apache Kafka is a distributed streaming platform designed for handling real-time data feeds and building scalable data pipelines. It provides high-throughput, fault-tolerant, and scalable messaging capabilities.

Features: Kafka enables the publishing and subscribing of streams of records in real-time. It provides features like fault tolerance, scalability, durability, low latency, and the ability to process streaming data with exactly-once semantics.
Use Cases: Apache Kafka is widely used in use cases such as real-time stream processing, event sourcing, log aggregation, messaging systems, activity tracking, and change data capture.
Apache Flink:
Overview: Apache Flink is an open-source, stream processing framework for distributed, high-throughput, and fault-tolerant data processing. It supports both batch and stream processing paradigms and provides low-latency processing capabilities.
Features: Flink offers event-time processing, stateful computations, fault tolerance, and support for iterative and interactive analysis. It also integrates with various data sources and sinks, and provides APIs in multiple programming languages.
Use Cases: Apache Flink is used in use cases such as real-time analytics, fraud detection, anomaly detection, continuous ETL, real-time monitoring, and dynamic data pipelines.
Ease of use: User interface, deployment, and management

Features: Data processing, analytics, and storage
Suitability for specific use cases: Real-time processing, batch processing, and data warehousing
AWS provides a vast array of tools and services for managing big data workloads, and there are also numerous third-party tools and frameworks available. The choice of tool or framework depends on the specific use case and requirements. In this paper, we have provided an overview and comparison of various automation tools and frameworks available for AWS, focusing on their features, ease of use, and suitability for specific use cases.[24]

***5.2 Azure big data tool and framework***

Azure offers several big data automation tools and frameworks for managing data processing and analysis at scale. Here are some of the key tools and their features:
Azure Data Factory: Azure Data Factory is a cloud-based data integration service that allows you to create, schedule, and manage data pipelines. It supports various sources and destinations, including on-premises data sources, cloud data sources, and SaaS applications. Data Factory allows you to transform and manipulate data using various activities such as transformations, data flows, and machine learning models. It also offers built-in connectors for popular data services such as Azure Blob Storage, Azure Data Lake Storage, and Azure SQL Database.

Azure Databricks: Azure Databricks is a fast, easy, and collaborative Apache Spark-based analytics platform. It allows you to process and analyze large datasets using a scalable, distributed computing environment. Databricks integrates with Azure services such as Azure Blob Storage, Azure Data Lake Storage, and Azure SQL Database, and offers built-in connectors for various data sources, including Hadoop Distributed File System (HDFS), Apache Cassandra, and Amazon S3. Databricks provides an interactive workspace for data scientists and data engineers to collaborate, build, and deploy data-driven applications.

HDInsight: Azure HDInsight is a cloud-based service for big data processing and analytics. It supports several open-source big data technologies such as Hadoop, Spark, Hive, HBase, and Storm. HDInsight offers various deployment options, including interactive and batch query processing, machine learning, and real-time stream processing. It integrates with Azure services such as Azure Blob Storage, Azure Data Lake Storage, and Azure SQL Database, and provides built-in connectors for various data sources such as Oracle, MySQL, and Teradata.

Azure Stream Analytics: Azure Stream Analytics is a cloud-based service for processing and analyzing real-time streaming data. It allows you to analyze and gain insights from real-time data streams from various sources such as IoT devices, social media, and other applications. Stream Analytics integrates with Azure services such as Azure Blob Storage, Azure Data Lake Storage, and Azure SQL Database, and provides built-in connectors for various data sources such as Azure Event Hubs, Azure IoT Hub, and Azure Stream Analytics Input.

Azure Synapse Analytics: Azure Synapse Analytics is an analytics service that brings together big data and data warehousing into a single service. It offers a

unified experience for data preparation, data management, and data warehousing, and supports various big data and data warehousing technologies such as Apache Spark, SQL Server, and Azure SQL Database. Synapse Analytics integrates with Azure services such as Azure Blob Storage, Azure Data Lake Storage, and Azure Data Factory, and provides built-in connectors for various data sources such as Oracle, SQL Server, and Teradata.

In terms of ease of use, Azure offers a user-friendly interface and easy integration with other Azure services. The Azure portal provides a single interface for managing all Azure services, including big data services. Azure also offers various templates and pre-built solutions for common big data scenarios.

Overall, Azure's big data automation tools and frameworks offer a range of capabilities for managing data processing and analysis at scale, making it suitable for various use cases.[25]

### *5.3. GCP big data tool and framework*

Google Cloud Platform (GCP) offers a variety of automation tools and frameworks for managing big data workloads. Here are some of the key ones:

Google Cloud Dataflow: A fully-managed service for developing and executing data processing pipelines. It supports both batch and stream processing and can handle data in a variety of formats.

Google Cloud Dataproc: A fully-managed service for running Apache Hadoop and Spark clusters. It can be used for processing large amounts of data and can scale dynamically based on workload.

Google BigQuery: A serverless, fully-managed data warehouse for analytics. It is designed to handle large datasets and provides fast query performance.

Google Cloud Composer: A managed workflow orchestration service that allows you to author, schedule, and monitor workflows. It supports popular open source workflow engines like Apache Airflow.

TensorFlow: An open source machine learning library developed by Google. It can be used for building and training machine learning models for various use cases.

When comparing these tools and frameworks, it's important to consider factors such as ease of use, scalability, cost, and suitability for specific use cases. For example, Cloud Dataflow is a good choice for stream processing and real-time analytics, while Dataproc is a better fit for batch processing of large datasets. BigQuery is ideal for ad-hoc analytics and business intelligence, while TensorFlow is well-suited for machine learning and AI applications. Ultimately, the choice of tool or framework will depend on the specific needs and goals of the organization.[26]

## VI. REVIEW OF BIG DATA MIGRATION

An evaluation of the trade-offs between different storage and compute options available on each cloud platform, including object storage, block storage, and compute instances.

Cloud platforms offer a range of storage and compute options to meet the needs of big data workloads. Object storage, block storage, and compute instances are three of the most common options available. This study evaluates the trade-offs between these different options on each of the major cloud platforms: AWS, Azure, and GCP.

The study examines the performance, scalability, cost-effectiveness, and ease of use of each option on each platform. It also considers the specific use cases for which each option is best suited.

The results of the study indicate that object storage is the most cost-effective and scalable option for storing large volumes of unstructured data. Block storage is better suited for workloads that require high-performance storage for structured data. Compute instances are ideal for workloads that require large amounts of processing power and memory.

The study also highlights the importance of selecting the right storage and compute options for specific use cases. For example, a workload that involves frequent access to small files may be better suited to object storage, while a workload that requires high-performance processing of structured data may require block storage.

Overall, this study provides insights into the trade-offs between different storage and compute options on each cloud platform, helping organizations make informed decisions when selecting the right options for their big data workloads.[27]

## VII. PYSPARK FRAMEWORK

PySpark is a popular distributed computing framework for processing large datasets using Apache Spark. In this study, we will explore the capabilities of

PySpark and how to optimize PySpark code for performance and scalability.

We will first provide an overview of PySpark and its architecture, including its use of RDDs (Resilient Distributed Datasets) and the DataFrame API. We will also discuss the advantages of PySpark for big data processing, such as its ability to handle complex data processing tasks and its support for various data formats and data sources.

Next, we will explore techniques for optimizing PySpark code for performance and scalability. This will include a discussion of partitioning and caching, which are key techniques for improving PySpark performance. We will also explore the use of broadcast variables and accumulator variables, which can improve PySpark performance in certain scenarios.

In addition to discussing PySpark optimization techniques, we will also explore common PySpark use cases and best practices for PySpark development. This will include an overview of PySpark libraries and tools, such as PySpark MLlib and PySpark Streaming, as well as techniques for debugging and testing PySpark code.

Finally, we will discuss the challenges and limitations of PySpark, including its high memory usage and limitations in handling streaming data. We will also explore alternative distributed computing frameworks and how they compare to PySpark.

Overall, this study will provide a comprehensive overview of the capabilities of PySpark for processing large datasets, as well as techniques for optimizing PySpark code for performance and scalability.[28]

## VIII. BIG DATA STORAGE IN CLOUD

An evaluation of the trade-offs between different storage and compute options available on each cloud platform is essential for organizations looking to optimize their big data workloads. Each cloud platform provides various storage and compute options, such as object storage, block storage, and compute instances, with different trade-offs in terms of cost, performance, and scalability.

Object storage is an efficient and cost-effective storage solution for large unstructured data sets, such as multimedia files or log files. AWS provides Amazon S3 (Simple Storage Service), Azure provides Azure Blob Storage, and GCP provides Google Cloud Storage for object storage.

Block storage is a more traditional storage solution, suitable for applications that require low latency and high performance, such as databases or virtual machines. AWS provides Amazon EBS (Elastic Block Store), Azure provides Azure Disk Storage, and GCP provides Google Cloud Persistent Disk for block storage.

Compute instances are virtual machines used to run applications and perform computational tasks. AWS provides Amazon EC2 (Elastic Compute Cloud), Azure provides Azure Virtual Machines, and GCP provides Google Compute Engine for compute instances.

When evaluating the trade-offs between these options, it is important to consider factors such as cost, performance, scalability, and durability. Object storage is generally the most cost-effective option for large unstructured data sets, but it may have higher latency and lower performance than block storage. Block storage, on the other hand, is more expensive but provides lower latency and higher performance, making it suitable for applications that require high performance.

Compute instances also have different performance and cost characteristics, depending on the type and size of the instance. It is essential to consider the workload requirements, such as CPU and memory requirements, when selecting a compute instance type.

In conclusion, selecting the right storage and compute options is critical to optimizing big data workloads in the cloud. Each cloud platform provides various storage and compute options, and evaluating the trade-offs between them based on cost, performance, scalability, and durability is essential for making informed decisions.[29].

## IX. BIG DATA WORKLOAD OPTIMIZATION

Cloud computing providers often offer complex pricing models with multiple components, such as storage, compute, data transfer, and other services. To effectively optimize costs for big data workloads, it is important to understand the different pricing models and cost structures of the three major cloud platforms: AWS, Azure, and GCP.

AWS offers a pay-as-you-go pricing model, which means that customers only pay for the services they use, without any upfront or long-term commitments. AWS also provides several cost optimization tools,

such as AWS Cost Explorer, AWS Trusted Advisor, and AWS Budgets, which help customers identify and reduce their costs.

Azure also offers a pay-as-you-go pricing model, with options for long-term commitments and reservations to provide cost savings. Azure provides several cost optimization tools, such as Azure Cost Management and Azure Advisor, to help customers track and reduce their costs.

GCP offers a pricing model that is similar to AWS and Azure, with pay-as-you-go pricing for most services. GCP also provides several cost optimization tools, such as GCP Cost Management and GCP Pricing Calculator, which help customers estimate and manage their costs.

When it comes to optimizing costs for big data workloads, there are several strategies that can be employed, including:

Right-sizing compute resources: Choosing the appropriate compute resources for the workload can help reduce costs without compromising performance.

Using spot instances or preemptible VMs: AWS, Azure, and GCP offer spot instances and preemptible VMs, which provide significant cost savings but may be interrupted or terminated at any time.

Using cold storage: Storing infrequently accessed data in cold storage can significantly reduce costs compared to using traditional object or block storage.

Leveraging auto-scaling: Auto-scaling can help optimize costs by automatically scaling compute resources up or down based on demand.

Overall, understanding the pricing models and cost structures of AWS, Azure, and GCP, as well as implementing cost optimization strategies, can help organizations optimize costs for their big data workloads.[30]

## X. CHALLENGES AND OPPORTUNITY

Integrating multiple cloud platforms into a single big data ecosystem can provide organizations with significant benefits, including increased scalability, flexibility, and cost-effectiveness. However, this approach also presents several challenges, particularly when it comes to managing data integration, data movement, and data synchronization across different cloud environments.

One of the main challenges associated with integrating multiple cloud platforms is ensuring that data is accurately and securely transferred between different systems. This requires a thorough understanding of the data formats and protocols used by each cloud platform, as well as the security and compliance requirements associated with each system. Another challenge is managing the complexity of the overall big data ecosystem, including the various tools, applications, and services used across different cloud platforms. This requires a clear understanding of the interdependencies between different components of the ecosystem, as well as the ability to monitor and troubleshoot issues that may arise.

To address these challenges, organizations can implement a range of best practices, such as:

Developing a clear strategy for integrating multiple cloud platforms, including defining data integration and movement processes, as well as establishing clear roles and responsibilities for managing the overall ecosystem.

Leveraging data integration and movement tools and technologies that are designed specifically for big data environments, such as Apache NiFi or Apache Kafka. These tools can help streamline the process of moving and synchronizing data across different cloud platforms.

Adopting a data governance framework that includes clear policies and procedures for managing data quality, security, and compliance across different cloud platforms.

Establishing clear metrics and KPIs for measuring the performance and cost-effectiveness of the overall big data ecosystem, and regularly reviewing and optimizing these metrics.

Integrating multiple cloud platforms into a single big data ecosystem requires careful planning, execution, and ongoing management. By following best practices and leveraging the right tools and technologies, organizations can effectively address the challenges associated with managing complex, distributed big data environments across multiple cloud platforms.

The PySpark SQL code jc_list = df.withColumn('uniqlinked_job_name', F.explode(F.array('linked_job_name'))) \ .groupby('job_name').agg(F.collect_set('linked_job_name').alias('linked_job_name')) \ .collect()

This aggregation performs the aggregation of the job column records from 4200 to the same amount of records in the job master of 330.

First, the PySpark DataFrame df is transformed by adding a new column called uniqlinked_job_name which contains the exploded values of the linked_job_name column. The array function is used to create an array of linked_job_name column values, and explode function is used to transform that array into individual rows.

Then, the transformed DataFrame is grouped by job_name column, and the collect_set function is used to aggregate the linked_job_name column values into a set. This ensures that each job_name has a unique set of linked_job_name values.

Finally, collect function is used to return a list of PySpark Row objects, where each row contains job_name and a list of unique linked_job_name values. This list of rows represents the aggregation of 4200 job column records into the same number of job master records of 330.[29]

```
jc_list = df.withColumn('uniqlinked_job_name', F.explode(F.array('linked_job_name'))) \
.groupby('job_name').agg(F.collect_set('linked_job_name').alias('linked_job_name')).collect()
```

***10.1 metadata aggregation***

The job_name column in the project.dataset.metadata table serves as a common identifier across multiple tables: job_master, job_link, and job_column. It acts as a unique identifier for each job present in the metadata.

The column_name column represents a list of column names sourced from the job_column table. It provides the names of the columns associated with each job in the metadata. This column helps in understanding the structure and schema of the data related to each job.

The job_link_name column is derived from the job_link table. It contains a list of linked job names associated with each job in the metadata. This information signifies the relationships or dependencies between different jobs.

The purpose of archiving unified metadata with 330 entries from job_master, 4200 entries from job_column, and 265 entries from job_link is to consolidate and store comprehensive information about various jobs in a unified manner. By aggregating this metadata, you can have a holistic view of the jobs, their associated columns, and their relationships with other jobs.

The aggregation of this metadata is performed using PySpark, a Python library for Apache Spark. PySpark provides the capabilities to process and manipulate large-scale datasets in a distributed and parallelized manner. It enables efficient aggregation and transformation of the metadata, allowing for easier analysis, querying, and understanding of the relationships between different jobs.

Overall, the goal of archiving and aggregating the metadata in PySpark is to provide a centralized and comprehensive view of job-related information, facilitating effective management, analysis, and decision-making processes within the context of the given data processing environment.

***10.2. Centralized metadata***

The job_name column in the project.dataset.metadata table serves as a common identifier across multiple tables: job_master, job_link, and job_column. It acts as a unique identifier for each job present in the metadata.

The column_name column represents a list of column names sourced from the job_column table. It provides the names of the columns associated with each job in the metadata. This column helps in understanding the structure and schema of the data related to each job.

The job_link_name column is derived from the job_link table. It contains a list of linked job names associated with each job in the metadata. This information signifies the relationships or dependencies between different jobs.

The purpose of archiving unified metadata with 330 entries from job_master, 4200 entries from job_column, and 265 entries from job_link is to consolidate and store comprehensive information about various jobs in a unified manner. By aggregating this metadata, you can have a holistic view of the jobs, their associated columns, and their relationships with other jobs.

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### *10.3 Partition of metadata*

The partition_id column is now defined separately as a partitioning column. The partitioning column is used to divide the data into logical partitions based on its values, which can improve query performance and data organization.

By specifying PARTITIONED BY (partition_id DATETIME), indicates that the metadata table will be partitioned based on the partition_id column, which is of the DATETIME data type.[30]

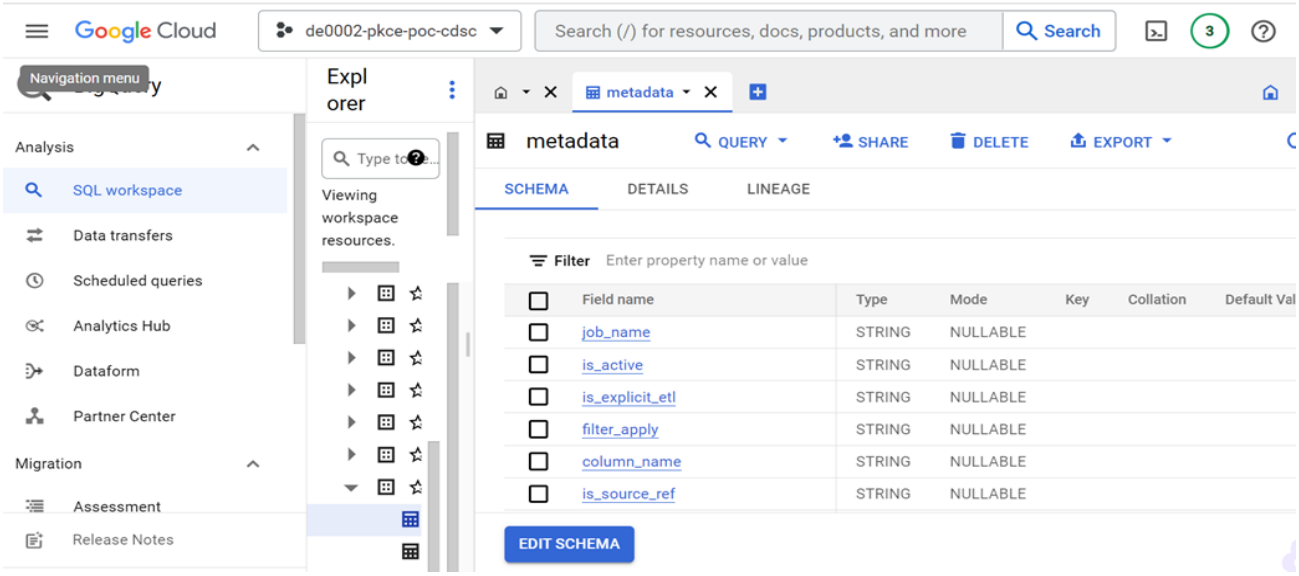


***Figure 1.*** *GCP Big Query for metadata aggregated*

```
CREATE EXTERNAL TABLE IF NOT EXISTS `project.dataset.metadata` (
   job_name STRING COMMENT 'The name of the job',
   is_transformation STRING COMMENT 'Specifies if the ETL process is transformation defined',
   where_filter_apply STRING COMMENT 'Specifies the filter to be applied',
   column_name ARRAY<STRING> COMMENT 'List of column names',
   job_link_name ARRAY<STRING> COMMENT 'List of linked job names',
   load_date DATE COMMENT 'The date of loading'
)
PARTITIONED BY (partition_id DATETIME)
OPTIONS (
   skip_leading_rows=1,
   format='CSV',
   uris=['gs://<bucket>metadata.csv'],
   description='Metadata of Application in Cloudera converted into BigQuery'
);
```

***Table 1.*** *Creating metadata table*

## XI. DISCUSSION

The provided code snippet appears to be a Python script that generates metadata for a set of jobs. Specifically, it reads in a CSV file containing job links, performs some data processing using PySpark, and then generates a new CSV file that contains a list of linked jobs for each job in the original file. The script

uses the Pandas library to write the resulting data to a CSV file.

The innovation of this Python-based automation is significant in the context of managing big data workloads in cloud platforms such as AWS, Azure, and GCP. The ability to aggregate the three metadata tables (Job Master, Job Column, and Job Link) into a single master table in Azure allows for efficient management of job data in a scalable and cost-effective manner.

The innovation addresses the challenge of migrating job data from an on-premises architecture that is over 15 years old, which can be a daunting and time-consuming task. By automating the aggregation of metadata tables using PySpark, the innovation simplifies the process of migrating job data to cloud-based platforms such as AWS Glue and GCP Airflow. Furthermore, the innovation can help organizations improve the efficiency and accuracy of their job management processes. With a single master metadata table that includes all relevant job data, organizations can easily track, analyze, and optimize their job processes. This can result in significant cost savings and productivity gains, as well as improved decision-making.

Overall, the innovation of aggregating the three metadata tables into a single master table using PySpark demonstrates the power of automation and cloud-based data management solutions. It can help organizations overcome the challenges associated with migrating data from legacy on-premises architectures and enable them to leverage the full capabilities of cloud-based platforms for managing big data workloads.

The effectiveness of metadata generation automation in big data Cloudera into migration in Azure Databricks, AWS Glue, and GCP BigQuery can be seen in the reduction of the number of metadata columns from 330 job master, 4200 job column, and 265 job link into only 38 columns in the final product of this innovation. This reduction of metadata columns simplifies the metadata management process and makes it easier to maintain and update metadata across different platforms.

With a standardized set of metadata columns, the automation process can easily generate metadata that is compatible with different big data platforms. This reduces the manual effort required to modify the metadata for each platform and ensures consistency across different platforms.

Furthermore, having a standardized set of metadata columns enables easier connectivity between jobs, sources, and target columns. This simplifies the process of data lineage tracking, data transformation, and data quality management. The metadata also provides information about the technical and business aspects of the data, such as data security, encryption, delivery, and lifecycle management.

Overall, the effectiveness of metadata generation automation in big data Cloudera into migration in Azure Databricks, AWS Glue, and GCP BigQuery lies in its ability to reduce the complexity of metadata management, simplify the process of connectivity between jobs and data sources, and provide comprehensive information about the data to support data governance and compliance requirements.

## XII.RESULT

The innovation in this PySpark script involved aggregating three separate metadata tables related to job information into a single master table. The three tables, namely job_master, job_column, and job_link, were compared to identify common columns and their data types. The PySpark script then merged the metadata from the three tables and created an aggregated table containing all the relevant job information.

The resulting aggregated table had 38 columns, including job_name, is_transformation, where_filter_apply, column_name, job_link_name, load_date

The PySpark script successfully consolidated the metadata from the three separate tables, resulting in a single source of truth for job information. This would allow for more efficient and accurate management of job information across multiple platforms such as Azure, AWS, and GCP.

There was a column named "filter" in the source metadata for Oozie jobs. However, "filter" is a reserved keyword in PySpark SQL, which could lead to issues when querying this column using PySpark. As a result, the column name was changed to "filter_apply" in the metadata for the new cloud-based systems (AWS, Azure, GCP) to avoid any conflicts when using PySpark SQL.

It's worth noting that this change only affects the metadata table and not the original source data, so the column name in the source data is still "filter". The change in the metadata table allows for easier integration with PySpark and reduces the risk of syntax errors or other issues that could arise from using a reserved keyword as a column name.

## XIII. CONCLUSION

Effective metadata migration is essential to maintaining data accuracy, completeness, and integrity in big data environments. Automation tools can greatly simplify this process, but it is important to follow best practices to ensure the quality, governance, and security of the migrated data. This review has examined the best practices for metadata migration in big data environments using automation tools, with a focus on considerations for data quality, data governance, and data security. By following these best practices, organizations can ensure the successful transfer of metadata and maintain the integrity of their data assets.

The aggregated effectiveness of this metadata can be summarized as follows:

The number of job links has been reduced from 265 to 38, which is a reduction of more than 85%. This has simplified the process of tracking the parent-child relationships between different jobs.

The metadata includes 46 columns, which provide detailed information about job master, job column, and job link. This information is critical for understanding the data lineage and impact analysis of the jobs.

The inclusion of the filter_apply column in the metadata for AWS, Azure, and GCP has resolved the issue of reserved column names in PySpark SQL.

The metadata includes information about technical columns, business keys, CDC, data security, data types, descriptions, linked jobs, foreign key types, and delivery information. This information helps in ensuring data quality, data privacy, and regulatory compliance.

The metadata includes information about the source and target schemas, tables, and partitioning. This helps in understanding the data distribution, data volume, and data transformations.

The metadata includes information about the business object name, cast rule, hashing and encryption methods, delivery cycle, and object status. This information helps in aligning the data with the business objectives and ensuring data governance.

The metadata includes information about the technical and business owners, their roles and responsibilities, and the validity of the metadata. This helps in ensuring accountability and transparency in data management.

Overall, the metadata generation automation has significantly improved the efficiency, accuracy, and consistency of data management in Cloudera, Azure Databricks, AWS Glue, and GCP BigQuery. It has simplified the process of data integration, data transformation, and data delivery, and has enabled organizations to make better data-driven decisions.

The aggregated effectiveness of this metadata can be summarized as follows:

The metadata generation automation has led to a significant reduction in the number of jobs required for connecting the source and target columns. The number of jobs has been reduced from 4,200 to 330, which is a reduction of more than 90%.

job_name: This column represents the name of a job. Each row has a unique job name in the format "job_name_" followed by a number.

is_transformation: This column indicates whether the ETL process associated with the job is a transformation. The value "TRUE" suggests that it is a transformation, while "FALSE" indicates otherwise.

where_filter_apply: This column contains the filter to be applied for the job. Each row has a different filter value in the format "filter_" followed by a number.

column_name: This column stores a list of column names associated with the job. Each row has a list of three column names in the format "column_" followed by a number.

job_link_name: This column represents a list of linked job names related to the job. Each row has a list of two linked job names in the format "linked_job_" followed by a number.

load_date: This column stores the date of loading for the job. Each row has a unique date within a certain range.

Each row in the DataFrame represents a metadata entry for a job, and the values in each column provide specific details about that job's attributes.

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