Using Apache Iceberg on AWS

AWS Prescriptive Guidance

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Amazon Web Services (contributors)

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Apache Iceberg is an open-source table format that simplifies table management while improving performance. AWS analytics services such as Amazon EMR, AWS Glue, Amazon Athena, and Amazon Redshift include native support for Iceberg, so you can easily build transactional data lakes on top of Amazon Simple Storage Service (Amazon S3) on AWS.

In addition, the next generation of Amazon SageMaker is built on an open lakehouse architecture that unifies data access across AWS data lakes, data warehouses, and third-party and federated sources. The lakehouse is fully compatible with Iceberg and gives you the flexibility to access and query data in place by using the Iceberg REST API.

This technical guide provides guidance on getting started with Iceberg on different AWS services, and includes best practices and recommendations for running Iceberg on AWS at scale while optimizing cost and performance.

Whether you're just starting out with Iceberg or you're an experienced user looking to optimize your existing Iceberg workloads on AWS, this guide offers valuable insights for every stage of your project

In this guide:

- Migrating existing tables to Iceberg
- Best practices for optimizing Iceberg workloads
- Monitoring Iceberg workloads
- Governance and access control
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Modern data lakes

Advanced use cases in modern data lakes

The evolution of data storage has progressed from databases to data warehouses and data lakes, where each technology addresses unique business and data requirements. Traditional databases excelled at handling structured data and transactional workloads, but they faced performance challenges as data volumes increased. Data warehouses emerged to tackle performance and scalability issues, but like databases, they relied on proprietary formats within vertically integrated systems.

Data lakes offer one of the best options for storing data in terms of cost, scalability, and flexibility. You can use a data lake to retain large volumes of structured and unstructured data at a low cost, and use this data for different types of analytics workloads, from business intelligence reporting to big data processing, real-time analytics, machine learning, and generative artificial intelligence (AI), to help guide better decisions.

Despite these benefits, data lakes weren't initially designed with database-like capabilities. A data lake doesn't provide support for atomicity, consistency, isolation, and durability (ACID) processing semantics, which you might require to optimize and manage your data effectively at scale across hundreds or thousands of users by using many different technologies. Data lakes don't provide native support for the following functionality:

- Performing efficient record-level updates and deletions as data changes in your business
- Managing query performance as tables grow to millions of files and hundreds of thousands of partitions
- Ensuring data consistency across multiple concurrent writers and readers
- Preventing data corruption when write operations fail partway through the operation
- Evolving table schemas over time without (partially) rewriting datasets

These challenges have become particularly prevalent in use cases such as handling change data capture (CDC) or use cases pertaining to privacy, deletion of data, and streaming data ingestion, which can result in sub-optimal tables.

Data lakes that use the traditional Hive-format tables support write operations only for entire files. This makes updates and deletes difficult to implement, time consuming, and costly. Moreover, concurrency controls and guarantees offered in ACID-compliant systems are needed to ensure data integrity and consistency.

These challenges leave users with a dilemma: choose between a fully integrated but proprietary platform, or opt for a vendor-neutral but resource-intensive, self-built data lake that requires constant maintenance and migration to realize its potential value.

To help overcome these challenges, Iceberg provides additional database-like functionality that simplifies the optimization and management overhead of data lakes, while still supporting storage on cost-effective systems such as Amazon S3.

Introduction to Apache Iceberg

Apache Iceberg is an open-source table format that provides features in data lake tables that were historically only available in databases or data warehouses. It's designed for scale and performance, and is well-suited for managing tables that are over hundreds of gigabytes. Some of the main features of Iceberg tables are:

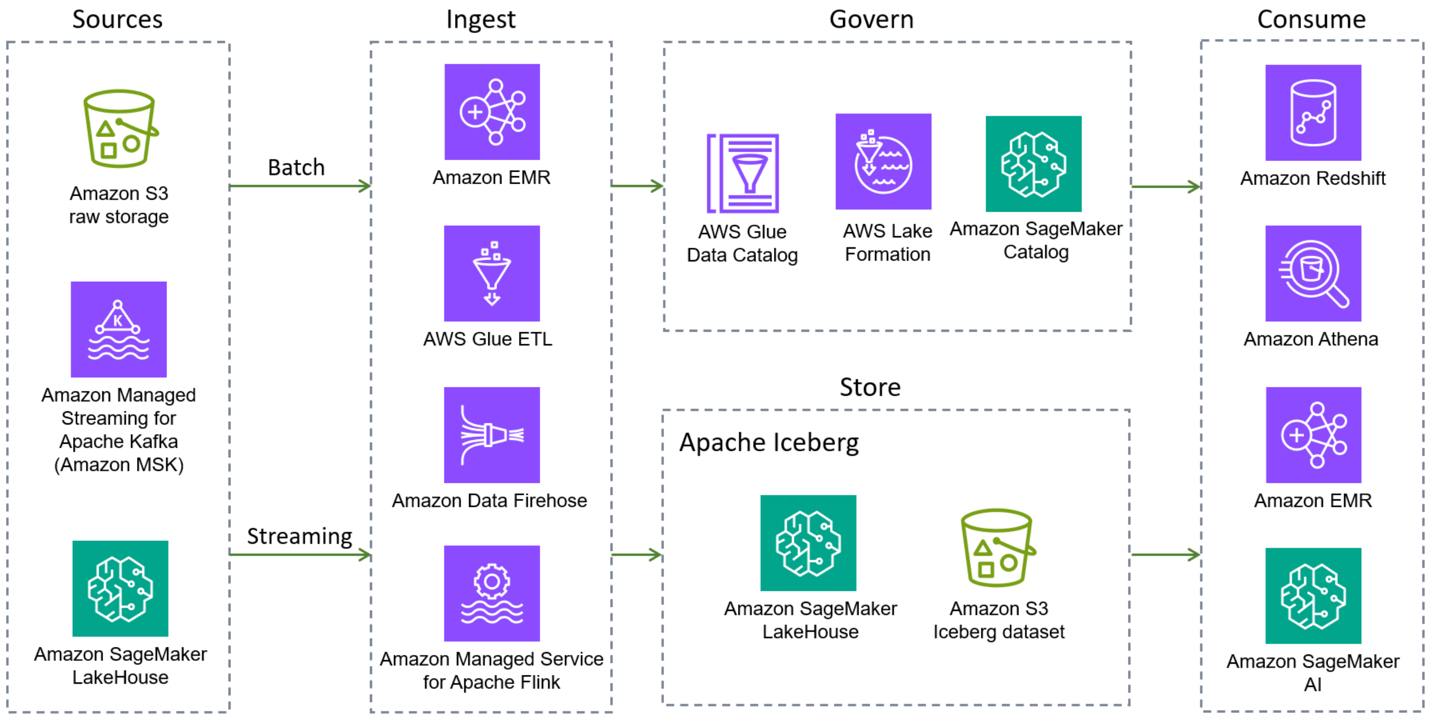
- **Delete, update, and merge.** Iceberg supports standard SQL commands for data warehousing for use with data lake tables.
- **Fast scan planning and advanced filtering.** Iceberg stores metadata such as partition and column-level statistics that can be used by engines to speed up planning and running queries.
- **Full schema evolution.** Iceberg supports adding, dropping, updating, or renaming columns without side-effects.
- **Partition evolution.** You can update the partition layout of a table as data volume or query patterns change. Iceberg supports changing the columns that a table is partitioned on, or adding columns to, or removing columns from, composite partitions.
- **Hidden partitioning.** This feature prevents reading unnecessary partitions automatically. This eliminates the need for users to understand the table's partitioning details or to add extra filters to their queries.
- **Version rollback.** Users can quickly correct problems by reverting to a pre-transaction state.
- **Time travel.** Users can query a specific previous version of a table.
- **Serializable isolation.** Table changes are atomic, so readers never see partial or uncommitted changes.
- **Concurrent writers.** Iceberg uses optimistic concurrency to allow multiple transactions to succeed. In case of conflicts, one of the writers has to retry the transaction.

- **Open file formats.** Iceberg supports multiple open source file formats, including Apache Parquet, Apache Avro, and Apache ORC.

In summary, data lakes that use the Iceberg format benefit from transactional consistency, speed, scale, and schema evolution. For more information about these and other Iceberg features, see the Apache Iceberg documentation.

AWS support for Apache Iceberg

Apache Iceberg is supported by AWS services such as Amazon EMR, Amazon Athena, Amazon Redshift, AWS Glue, and Amazon SageMaker. The following diagram depicts a simplified reference architecture of a data lake that's based on Iceberg.



The following AWS services provide native Iceberg integrations. There are additional AWS services that can interact with Iceberg, either indirectly or by packaging the Iceberg libraries.

- Amazon S3 is the best place to build data lakes because of its durability, availability, scalability, security, compliance, and audit capabilities. Iceberg was designed and built to interact with Amazon S3 seamlessly, and provides support for many Amazon S3 features as listed in the Iceberg documentation. In addition, Amazon S3 Tables deliver the first cloud object store with built-in Iceberg support and streamline storing tabular data at scale. With S3 Tables support for Iceberg, you can easily query your tabular data by using popular AWS and third-party query engines.

- The next generation of SageMaker is built on an open lakehouse architecture that unifies data access across Amazon S3 data lakes, Amazon Redshift data warehouses, and third-party and federated data sources. These capabilities help you build powerful analytics and AI/ML applications on a single copy of data. The lakehouse is fully compatible with Iceberg, so you have the flexibility to access and query data in place by using the Iceberg REST API.
- Amazon EMR is a big data solution for petabyte-scale data processing, interactive analytics, and machine learning by using open source frameworks such as Apache Spark, Flink, Trino, and Hive. Amazon EMR can run on customized Amazon Elastic Compute Cloud (Amazon EC2) clusters, Amazon Elastic Kubernetes Service (Amazon EKS), AWS Outposts, or Amazon EMR Serverless.
- Amazon Athena is a serverless, interactive analytics service that's built on open source frameworks. It supports open-table and file formats and provides a simplified, flexible way to analyze petabytes of data where it lives. Athena provides native support for read, time travel, write, and DDL queries for Iceberg and uses the AWS Glue Data Catalog for the Iceberg metastore.
- Amazon Redshift is a petabyte-scale cloud data warehouse that supports both cluster-based and serverless deployment options. Amazon Redshift Spectrum can query external tables that are registered with the AWS Glue Data Catalog and stored on Amazon S3. Redshift Spectrum also provides support for the Iceberg storage format.
- AWS Glue is a serverless data integration service that makes it easier to discover, prepare, move, and integrate data from multiple sources for analytics, machine learning (ML), and application development. It is fully integrated with Iceberg. Specifically, you can perform read and write operations on Iceberg tables by using AWS Glue jobs, manage tables through the AWS Glue Data Catalog (Hive metastore-compatible), discover and register tables automatically by using AWS Glue crawlers, and evaluate data quality in Iceberg tables through the AWS Glue Data Quality feature. The AWS Glue Data Catalog also supports collecting column statistics, calculating and updating the number of distinct values (NDVs) for each column in Iceberg tables, and automatic table optimizations (compaction, snapshot retention, orphan file deletion). AWS Glue also supports zero-ETL integrations from a list of AWS services and third-party applications into Iceberg tables.
- Amazon Data Firehose is a fully managed service for delivering real-time streaming data to destinations such as Amazon S3, Amazon Redshift, Amazon OpenSearch Service, Amazon OpenSearch Serverless, Splunk, Apache Iceberg tables, and any custom HTTP or HTTP endpoints owned by supported third-party service providers, including Datadog, Dynatrace, LogicMonitor,

MongoDB, New Relic, Coralogix, and Elastic. With Firehose, you don't need to write applications or manage resources. You configure your data producers to send data to Firehose, and it automatically delivers the data to the destination that you specified. You can also configure Firehose to transform your data before delivering it.

- Amazon Managed Service for Apache Flink is a fully managed Amazon service that lets you use an Apache Flink application to process streaming data. It supports both reading from and writing to Iceberg tables, and enables real-time data processing and analytics.
- Amazon SageMaker AI supports the storage of feature sets in Amazon SageMaker AI Feature Store by using Iceberg format.
- AWS Lake Formation provides coarse and fine-grained access control permissions to access data, including Iceberg tables consumed by Athena or Amazon Redshift. To learn more about permissions support for Iceberg tables, see the Lake Formation documentation.

AWS has a wide range of services that support Iceberg, but covering all these services is beyond the scope of this guide. The following sections cover Spark (batch and structured streaming) on Amazon EMR and AWS Glue, as well as Athena SQL. The following section provides a quick look at Iceberg support in Athena SQL.

Getting started with Iceberg tables in Amazon Athena SQL

Amazon Athena provides built-in support for Iceberg. You can use Iceberg without any additional steps or configuration except for setting up the service prerequisites detailed in the Getting started section of the Athena documentation. This section provides a brief introduction to creating tables in Athena. For more information, see Working with Iceberg tables by using Athena SQL later in this guide.

You can create Iceberg tables on AWS by using different engines. Those tables work seamlessly across AWS services. To create your first Iceberg tables with Athena SQL, you can use the following boilerplate code.

```
CREATE TABLE <table_name> (
    col_1 string,
    col_2 string,
    col_3 bigint,
    col_ts timestamp)
PARTITIONED BY (col_1, <<<partition_transform>>>(col_ts))
LOCATION 's3://<bucket>/<folder>/<table_name>/'
TBLPROPERTIES (
    'table_type' ='ICEBERG'
)
```

The following sections provide examples of creating partitioned and unpartitioned Iceberg table in Athena. For more information, see the Iceberg syntax detailed in the Athena documentation.

Creating an unpartitioned table

The following example statement customizes the boilerplate SQL code to create an unpartitioned Iceberg table in Athena. You can add this statement to the query editor in the Athena console to create the table.

```
CREATE TABLE athena_iceberg_table (
    color string,
    date string,
    name string,
    price bigint,
    product string,
    ts timestamp)
LOCATION 's3://DOC_EXAMPLE_BUCKET/ice_warehouse/iceberg_db/athena_iceberg_table/'
TBLPROPERTIES (
    'table_type' ='ICEBERG'
)
```

For step-by-step instructions for using the query editor, see Getting started in the Athena documentation.

Creating a partitioned table

The following statement creates a partitioned table based on the date by using Iceberg's concept of hidden partitioning. It uses the `day()` transform to derive daily partitions, using the `dd-mm-yyyy` format, out of a timestamp column. Iceberg doesn't store this value as a new column in the dataset. Instead, the value is derived on the fly when when you write or query data.

```
CREATE TABLE athena_iceberg_table_partitioned (
    color string,
    date string,
    name string,
    price bigint,
    product string,
    ts timestamp)
PARTITIONED BY (day(ts))
LOCATION 's3://DOC_EXAMPLE_BUCKET/ice_warehouse/iceberg_db/athena_iceberg_table/'
TBLPROPERTIES (
    'table_type' ='ICEBERG'
)
```

Creating a table and loading data with a single CTAS statement

In the partitioned and unpartitioned examples in the previous sections, the Iceberg tables are created as empty tables. You can load data to the tables by using the `INSERT` or `MERGE` statement. Alternatively, you can use a `CREATE TABLE AS SELECT (CTAS)` statement to create and load data into an Iceberg table in a single step.

CTAS is the best way in Athena to create a table and load data in a single statement. The following example illustrates how to use CTAS to create an Iceberg table (`iceberg_ctas_table`) from an existing Hive/Parquet table (`hive_table`) in Athena.

```
CREATE TABLE iceberg_ctas_table WITH (
  table_type = 'ICEBERG',
  is_external = false,
  location = 's3://DOC_EXAMPLE_BUCKET/ice_warehouse/iceberg_db/iceberg_ctas_table/'
) AS
SELECT * FROM "iceberg_db"."hive_table" limit 20
---
SELECT * FROM "iceberg_db"."iceberg_ctas_table" limit 20
```

To learn more about CTAS, see the Athena CTAS documentation.

Inserting, updating, and deleting data

Athena supports different ways of writing data to an Iceberg table by using the `INSERT INTO`, `UPDATE`, `MERGE INTO`, and `DELETE FROM` statements.

Note

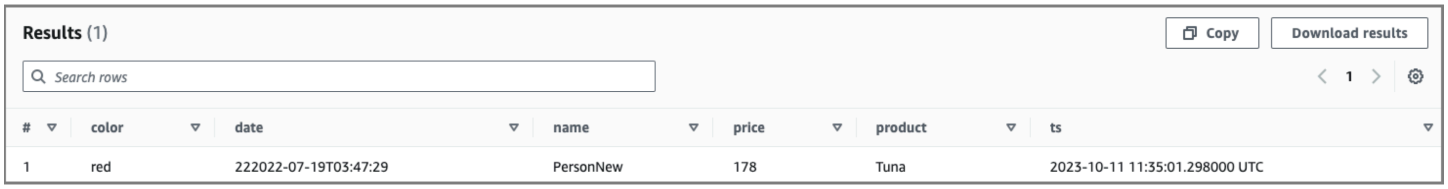
Athena SQL doesn't currently support the copy-on-write approach. `UPDATE`, `MERGE INTO`, and `DELETE FROM` operations always use the merge-on-read approach with positional deletes, regardless of specified table properties. If you set up table properties such as `write.update.mode`, `write.merge.mode`, and `write.delete.mode` to use copy-on-write, your queries won't fail, but Athena will ignore them and keep using merge-on-read.

The following statement uses `INSERT INTO` to add data to an Iceberg table:

```
INSERT INTO "iceberg_db"."ice_table" VALUES (
    'red', '222022-07-19T03:47:29', 'PersonNew', 178, 'Tuna', now()
)

SELECT * FROM "iceberg_db"."ice_table"
where color = 'red' limit 10;
```

Sample output:



#	color	date	name	price	product	ts
1	red	222022-07-19T03:47:29	PersonNew	178	Tuna	2023-10-11 11:35:01.298000 UTC

For more information, see the Athena documentation.

Querying Iceberg tables

You can run regular SQL queries against your Iceberg tables by using Athena SQL, as illustrated in the previous example.

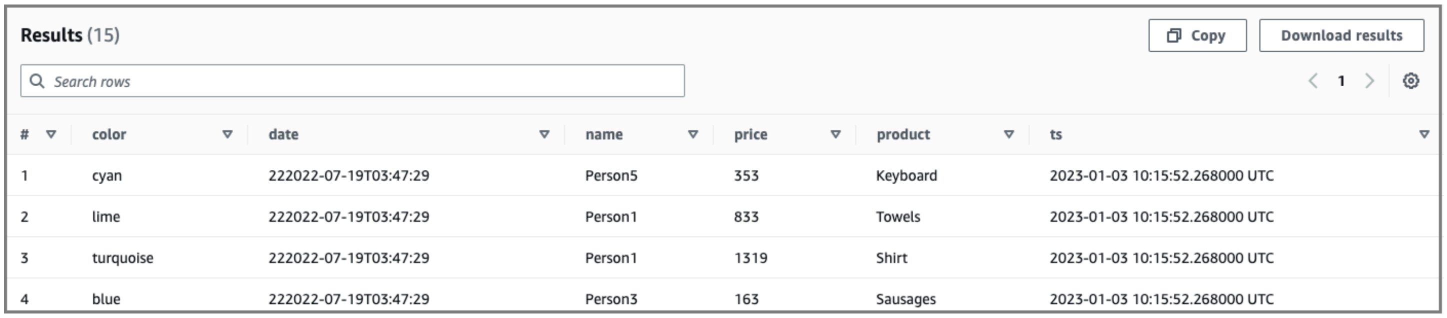
In addition to the usual queries, Athena also supports time travel queries for Iceberg tables. As discussed previously, you can change existing records through updates or deletes in an Iceberg table, so it's convenient to use time travel queries to look back into older versions of your table based on a timestamp or a snapshot ID.

For example, the following statement updates a color value for `Person5`, and then displays an earlier value from January 4, 2023:

```
UPDATE ice_table SET color='new_color' WHERE name='Person5'

SELECT * FROM "iceberg_db"."ice_table" FOR TIMESTAMP AS OF TIMESTAMP '2023-01-04
 12:00:00 UTC'
```

Sample output:



#	color	date	name	price	product	ts
1	cyan	222022-07-19T03:47:29	Person5	353	Keyboard	2023-01-03 10:15:52.268000 UTC
2	lime	222022-07-19T03:47:29	Person1	833	Towels	2023-01-03 10:15:52.268000 UTC
3	turquoise	222022-07-19T03:47:29	Person1	1319	Shirt	2023-01-03 10:15:52.268000 UTC
4	blue	222022-07-19T03:47:29	Person3	163	Sausages	2023-01-03 10:15:52.268000 UTC

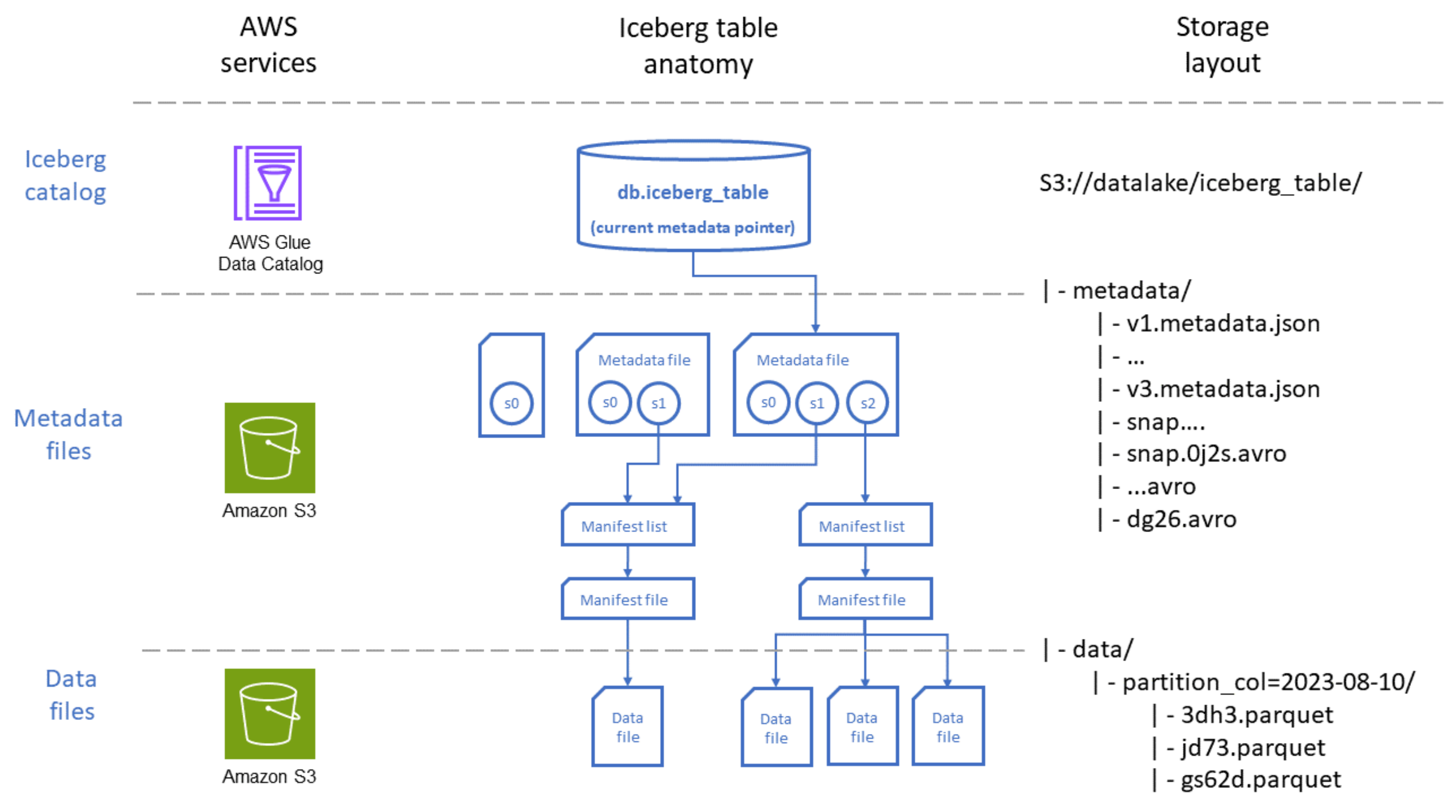
For syntax and additional examples of time travel queries, see the Athena documentation.

Iceberg table anatomy

Now that we've covered the basic steps of working with Iceberg tables, let's dive deeper into the intricate details and design of an Iceberg table.

To enable the features described earlier in this guide, Iceberg is designed with hierarchical layers of data and metadata files. These layers manage metadata intelligently to optimize query planning and execution.

The following diagram portrays the organization of an Iceberg table through two perspectives: the AWS services used to store the table and the file placement in Amazon S3.



As shown in the diagram, an Iceberg table consists of three main layers:

- **Iceberg catalog**: AWS Glue Data Catalog integrates natively with Iceberg and is, for most use cases, the best option for workloads that run on AWS. Services that interact with Iceberg tables (for example, Athena) use the catalog to find the current snapshot version of the table, either to read or to write data.
- **Metadata layer**: Metadata files, namely the manifest files and manifest list files, keep track of information such as the schema of the tables, the partition strategy, and the location of the data files, as well as column-level statistics such as minimum and maximum ranges for the records that are stored in each data file. These metadata files are stored in Amazon S3 within the table path.
  - **Manifest files** contain a record for each data file, including its location, format, size, checksum, and other relevant information.
  - **Manifest lists** provide an index of the manifest files. As the number of manifest files grows in a table, breaking up that information into smaller subsections helps reduce the number of manifest files that need to be scanned by queries.

  - **Metadata files** contain information about the whole Iceberg table, including the manifest lists, the schemas, partition metadata, snapshot files, and other files that are used to manage the table's metadata.
- **Data layer**: This layer contains the files that have the data records that queries will run against. These files can be stored in different formats, including Apache Parquet, Apache Avro, and Apache ORC.
  - **Data files** contain the data records for a table.
  - **Delete files** encode row-level delete and update operations in an Iceberg table. Iceberg has two types of delete files, as described in the Iceberg documentation. These files are created by operations by using the merge-on-read mode.

Working with Iceberg in Amazon EMR

Amazon EMR provides petabyte-scale data processing, interactive analytics, and machine learning in the cloud by using open source frameworks such as Apache Spark, Apache Hive, Flink, and Trino.

Note

This guide uses Apache Spark for examples.

Amazon EMR supports multiple deployment options: Amazon EMR on EC2, Amazon EMR on EKS, Amazon EMR Serverless, and Amazon EMR on AWS Outposts. To choose a deployment option for your workload, see the Amazon EMR FAQ.

Version and feature compatibility

Amazon EMR version 6.5.0 and later versions support Apache Iceberg natively. For a list of supported Iceberg versions for each Amazon EMR release, see Iceberg release history in the Amazon EMR documentation. Also review the sections under Use a cluster with Iceberg to see which Iceberg features are supported in Amazon EMR on different frameworks.

We recommend that you use the latest Amazon EMR version to benefit from the latest supported Iceberg version. The code examples and configurations in this section assume that you're using Amazon EMR release **emr-7.8.0**.

Creating an Amazon EMR cluster with Iceberg

To create an Amazon EMR cluster on Amazon EC2 with Iceberg installed, follow the instructions in the Amazon EMR documentation.

Specifically, your cluster should be configured with the following classification:

```
[{
    "Classification": "iceberg-defaults",
    "Properties": {
        "iceberg.enabled": "true"
    }
}]
```

You can also choose to use Amazon EMR Serverless or Amazon EMR on EKS as deployment options for your Iceberg workloads, starting from Amazon EMR 6.6.0.

Developing Iceberg applications in Amazon EMR

To develop the Spark code for your Iceberg applications, you can use Amazon EMR Studio, which is a web-based integrated development environment (IDE) for fully managed Jupyter notebooks that run on Amazon EMR clusters.

Using Amazon EMR Studio notebooks

You can interactively develop Spark applications in Amazon EMR Studio Workspace notebooks and connect those notebooks to your Amazon EMR on EC2 clusters or Amazon EMR on EKS managed endpoints. See AWS service documentation for instructions on setting up an EMR Studio for Amazon EMR on EC2 and Amazon EMR on EKS.

To use Iceberg in EMR Studio, follow these steps:

1. Launch an Amazon EMR cluster with Iceberg enabled, as instructed in Use a cluster with Iceberg Installed.
2. Set up an EMR Studio. For instructions, see Set up an Amazon EMR Studio.
3. Open an EMR Studio Workspace notebook and run the following code as the first cell in the notebook to configure your Spark session for using Iceberg:

```
%%configure -f
{
    "conf": {
        "spark.sql.catalog.<catalog_name>": "org.apache.iceberg.spark.SparkCatalog",
        "spark.sql.catalog.<catalog_name>.warehouse": "s3://YOUR-BUCKET-NAME/YOUR-
FOLDER-NAME/",
        "spark.sql.catalog.<catalog_name>.type": "glue",
        "spark.sql.extensions":
 "org.apache.iceberg.spark.extensions.IcebergSparkSessionExtensions"
    }
}
```

   where:

   - `<catalog_name>` is your Iceberg Spark session catalog name. Replace it with a name of your choice, and remember to change the references throughout all configurations that are associated with this catalog. In your code, you can refer to your Iceberg tables by using the fully qualified table name, including the Spark session catalog name, as follows:

```
<catalog_name>.<database_name>.<table_name>
```

Alternatively, you can change the default catalog to the Iceberg catalog that you defined by setting `spark.sql.defaultCatalog` to your catalog name. This second approach enables you to refer to tables without the catalog prefix, which can simplify your queries.

- `<catalog_name>.warehouse` points to the Amazon S3 path where you want to store your data and metadata.
- To make the catalog an AWS Glue Data Catalog, set `spark.sql.catalog.<catalog_name>.type` to `glue`. This key is required to point to an implementation class for any custom catalog implementation. The General best practices section later in this guide describes the different Iceberg-supported catalogs.

4. You can now start interactively developing your Spark application for Iceberg in the notebook, as you would for any other Spark application.

For more information about configuring Spark for Apache Iceberg by using Amazon EMR Studio, see the blog post Build a high-performance, ACID compliant, evolving data lake using Apache Iceberg on Amazon EMR.

Running Iceberg jobs in Amazon EMR

After you develop the Spark application code for your Iceberg workload, you can run it on any Amazon EMR deployment option that supports Iceberg (see the Amazon EMR FAQ).

As with other Spark jobs, you can submit work to an Amazon EMR on EC2 cluster by adding steps or by interactively submitting Spark jobs to the master node. To run a Spark job, see the following Amazon EMR documentation pages:

- For an overview of the different options for submitting work to an Amazon EMR on EC2 cluster and detailed instructions for each option, see Submit work to a cluster.
- For Amazon EMR on EKS, see Running Spark jobs with StartJobRun.
- For EMR Serverless, see Running jobs.

The following sections provide an example for each Amazon EMR deployment option.

Amazon EMR on EC2

You can use these steps to submit the Iceberg Spark job:

1. Create the file `emr_step_iceberg.json` with the following content on your workstation:

```
[{
    "Name": "iceberg-test-job",
    "Type": "spark",
    "ActionOnFailure": "CONTINUE",
    "Args": [
        "--deploy-mode",
        "client",
        "--conf",
        
  "spark.sql.extensions=org.apache.iceberg.spark.extensions.IcebergSparkSessionExtensions",
        "--conf",
        "spark.sql.catalog.<catalog_name>=org.apache.iceberg.spark.SparkCatalog",
        "--conf",
        "spark.sql.catalog.<catalog_name>.type=glue",
        "--conf",
        "spark.sql.catalog.<catalog_name>.warehouse=s3://YOUR-BUCKET-NAME/YOUR-
FOLDER-NAME/",
        "s3://YOUR-BUCKET-NAME/code/iceberg-job.py"
    ]
}]
```

2. Modify the configuration file for your specific Spark job by customizing the Iceberg configuration options that are highlighted in bold.
3. Submit the step by using the AWS Command Line Interface (AWS CLI). Run the command in the directory where the `emr_step_iceberg.json` file is located.

```
aws emr add-steps --cluster-id <cluster_id> --steps file://emr_step_iceberg.json
```

Amazon EMR Serverless

To submit an Iceberg Spark job to EMR Serverless by using the AWS CLI:

1. Create the file `emr_serverless_iceberg.json` with the following content on your workstation:

```
{
    "applicationId": "<APPLICATION_ID>",
    "executionRoleArn": "<ROLE_ARN>",
    "name": "iceberg-test-job",
    "jobDriver": {
        "sparkSubmit": {
            "entryPoint": "s3://YOUR-BUCKET-NAME/code/iceberg-job.py",
            "entryPointArguments": []
        }
    },
    "configurationOverrides": {
        "applicationConfiguration": [{
            "classification": "spark-defaults",
            "properties": {
                "spark.sql.extensions":
 "org.apache.iceberg.spark.extensions.IcebergSparkSessionExtensions",
                "spark.sql.catalog.<catalog_name>":
 "org.apache.iceberg.spark.SparkCatalog",
                "spark.sql.catalog.<catalog_name>.type": "glue",
                "spark.sql.catalog.<catalog_name>.warehouse": "s3://YOUR-BUCKET-NAME/
YOUR-FOLDER-NAME/",
                "spark.jars":"/usr/share/aws/iceberg/lib/iceberg-spark3-runtime.jar",

 "spark.hadoop.hive.metastore.client.factory.class":"com.amazonaws.glue.catalog.metastore.AWS
            }
        }],
        "monitoringConfiguration": {
            "s3MonitoringConfiguration": {
                "logUri": "s3://YOUR-BUCKET-NAME/emr-serverless/logs/"
            }
        }
    }
}
```

2. Modify the configuration file for your specific Spark job by customizing the Iceberg configuration options that are highlighted in bold.
3. Submit the job by using the AWS CLI. Run the command in the directory where the `emr_serverless_iceberg.json` file is located:

```
aws emr-serverless start-job-run --cli-input-json file://emr_serverless_iceberg.json
```

To submit an Iceberg Spark job to EMR Serverless by using the EMR Studio console:

1. Follow the instructions in the EMR Serverless documentation.
2. For **Job configuration**, use the Iceberg configuration for Spark provided for the AWS CLI and customize the highlighted fields for Iceberg. For detailed instructions, see Using Apache Iceberg with EMR Serverless in the Amazon EMR documentation.

Amazon EMR on EKS

To submit an Iceberg Spark job to Amazon EMR on EKS by using the AWS CLI:

1. Create the file `emr_eks_iceberg.json` with the following content on your workstation:

```
{
    "name": "iceberg-test-job",
    "virtualClusterId": "<VIRTUAL_CLUSTER_ID>",
    "executionRoleArn": "<ROLE_ARN>",
    "releaseLabel": "emr-6.9.0-latest",
    "jobDriver": {
        "sparkSubmitJobDriver": {
            "entryPoint": "s3://YOUR-BUCKET-NAME/code/iceberg-job.py",
            "entryPointArguments": [],
            "sparkSubmitParameters": "--jars local:///usr/share/aws/iceberg/lib/
iceberg-spark3-runtime.jar"
        }
    },
    "configurationOverrides": {
        "applicationConfiguration": [{
            "classification": "spark-defaults",
            "properties": {
                "spark.sql.extensions":
 "org.apache.iceberg.spark.extensions.IcebergSparkSessionExtensions",
                "spark.sql.catalog.<catalog_name>":
 "org.apache.iceberg.spark.SparkCatalog",
                "spark.sql.catalog.<catalog_name>.type": "glue",
                "spark.sql.catalog.<catalog_name>.warehouse": "s3://YOUR-BUCKET-NAME/
YOUR-FOLDER-NAME/",
                "spark.hadoop.hive.metastore.client.factory.class":
 "com.amazonaws.glue.catalog.metastore.AWSGlueDataCatalogHiveClientFactory"
            }
        }],
        "monitoringConfiguration": {
            "persistentAppUI": "ENABLED",
            "s3MonitoringConfiguration": {
                "logUri": "s3://YOUR-BUCKET-NAME/emr-serverless/logs/"
            }
        }
    }
}
```

2. Modify the configuration file for your Spark job by customizing the Iceberg configuration options that are highlighted in bold.
3. Submit the job by using the AWS CLI. Run the following command in the directory where the `emr_eks_iceberg.json` file is located:

```
aws emr-containers start-job-run --cli-input-json file://emr_eks_iceberg.json
```

For detailed instructions, see Using Apache Iceberg with Amazon EMR on EKS in the Amazon EMR on EKS documentation.

Best practices for Amazon EMR

This section provides general guidelines for tuning Spark jobs in Amazon EMR to optimize reading and writing data to Iceberg tables. For Iceberg-specific best practices, see the Best practices section later in this guide.

- **Use the latest version of Amazon EMR** – Amazon EMR provides Spark optimizations out of the box with the Amazon EMR Spark runtime. AWS improves the performance of the Spark runtime engine with each new release.
- **Determine the optimal infrastructure for your Spark workloads** – Spark workloads might require different types of hardware for different job characteristics to ensure optimal performance. Amazon EMR supports several instance types (such as compute optimized, memory optimized, general purpose, and storage optimized) to cover all types of processing requirements. When you onboard new workloads, we recommend that you benchmark with general instance types such as M5 or M6g. Monitor the operating system (OS) and YARN metrics from Ganglia and Amazon CloudWatch to determine the system bottlenecks (CPU, memory, storage, and I/O) at peak load and choose appropriate hardware.
- **Tune `spark.sql.shuffle.partitions`** – Set the `spark.sql.shuffle.partitions` property to the total number of virtual cores (vCores) in your cluster or to a multiple of that

value (typically, 1 to 2 times the total number of vCores). This setting affects the parallelism of Spark when you use hash and range partitioning as the write distribution mode. It requests a shuffle before writing to organize the data, which ensures partition alignment.

- **Enable managed scaling –** For almost all use cases, we recommend that you enable managed scaling and dynamic allocation. However, if you have a workload that has a predictable pattern, we suggest that you disable automatic scaling and dynamic allocation. When managed scaling is enabled, we recommend that you use Spot Instances to reduce costs. Use Spot Instances for task nodes instead of core or master nodes. When you use Spot Instances, use instance fleets with multiple instance types per fleet to ensure spot availability.
- **Use broadcast join when possible –** Broadcast (mapside) join is the most optimal join, as long as one of your tables is small enough to fit in the memory of your smallest node (in the order of MBs) and you are performing an equi (=) join. All join types except for full outer joins are supported. A broadcast join broadcasts the smaller table as a hash table across all worker nodes in memory. After the small table has been broadcast, you cannot make changes to it. Because the hash table is locally in the Java virtual machine (JVM), it can be merged easily with the large table based on the join condition by using a hash join. Broadcast joins provide high performance because of minimal shuffle overhead.
- **Tune the garbage collector –** If garbage collection (GC) cycles are slow, consider switching from the default parallel garbage collector to G1GC for better performance. To optimize GC performance, you can fine-tune the GC parameters. To track GC performance, you can monitor it by using the Spark UI. Ideally, the GC time should be less than or equal to 1 percent of the total task runtime.

Working with Iceberg in AWS Glue

AWS Glue is a serverless data integration service that makes it easier to discover, prepare, move, and integrate data from multiple sources for analytics, machine learning (ML), and application development. One of the core capabilities of AWS Glue is its ability to perform extract, transform, and load (ETL) operations in a simple and cost-effective manner. This helps categorize your data, clean it, enrich it, and move it reliably between various data stores and data streams.

AWS Glue jobs encapsulate scripts that define transformation logic by using an Apache Spark or Python runtime. AWS Glue jobs can be run in both batch and streaming mode.

When you create Iceberg jobs in AWS Glue, depending on the version of AWS Glue, you can use either native Iceberg integration or a custom Iceberg version to attach Iceberg dependencies to the job.

Using native Iceberg integration

AWS Glue versions 3.0, 4.0, and 5.0 natively support transactional data lake formats such as Apache Iceberg, Apache Hudi, and Linux Foundation Delta Lake in AWS Glue for Spark. This integration feature simplifies the configuration steps required to start using these frameworks in AWS Glue.

To enable Iceberg support for your AWS Glue job, set the job: Choose the **Job details** tab for your AWS Glue job, scroll to **Job parameters** under **Advanced properties**, and set the key to `--datalake-formats` and its value to `iceberg`.

If you are authoring a job by using a notebook, you can configure the parameter in the first notebook cell by using the `%%configure` magic as follows:

```
%%configure
{
  "--conf" : <job-specific Spark configuration discussed later>,
  "--datalake-formats" : "iceberg"
}
```

The `iceberg` configuration for `--datalake-formats` in AWS Glue corresponds to specific Iceberg versions based on your AWS Glue version:

AWS Glue version	Default Iceberg version
5.0	1.7.1
4.0	1.0.0
3.0	0.13.1

Using a custom Iceberg version

In some situations, you might want to retain control over the Iceberg version for the job and upgrade it at your own pace. For example, upgrading to a later version can unlock access to new features and performance enhancements. To use a specific Iceberg version with AWS Glue, you can provide your own JAR files.

Before you implement a custom Iceberg version, verify compatibility with your AWS Glue environment by checking the AWS Glue versions section of the AWS Glue documentation. For example, AWS Glue 5.0 requires compatibility with Spark 3.5.4.

As an example, to run AWS Glue jobs that use Iceberg version 1.9.1, follow these steps:

1. Acquire and upload the required JAR files to Amazon S3:
   a. Download iceberg-spark-runtime-3.5_2.12-1.9.1.jar and iceberg-aws-bundle-1.9.1.jar from the Apache Maven repository.
   b. Upload these files to your designated S3 bucket location (for example, `s3://your-bucket-name/jars/`).
2. Set up the job parameters for your AWS Glue job as follows:
   a. Specify the complete S3 path to both JAR files in the `--extra-jars` parameter, separating them with a comma (for example, `s3://your-bucket-name/jars/iceberg-spark-runtime-3.5_2.12-1.9.1.jar,s3://your-bucket-name/jars/iceberg-aws-bundle-1.9.1.jar`).
   b. Do not include `iceberg` as a value for the `--datalake-formats` parameter.
   c. If you use AWS Glue 5.0, you must set the `--user-jars-first` parameter to `true`.

Spark configurations for Iceberg in AWS Glue

This section discusses the Spark configurations required to author an AWS Glue ETL job for an Iceberg dataset. You can set these configurations by using the `--conf` Spark key with a comma-separated list of all Spark configuration keys and values. You can use the `%%configure` magic in a notebook, or the **Job parameters** section of the AWS Glue Studio console.

```
%glue_version 5.0

%%configure
{
  "--conf" : "spark.sql.extensions=org.apache.iceberg.spark.extensions...",
  "--datalake-formats" : "iceberg"
}
```

Configure the Spark session with the following properties:

- `<catalog_name>` is the name of your Iceberg Spark session catalog name. Replace it with a name of your choice, and remember to change the references throughout all configurations that are associated with this catalog. In your code, you can refer to your Iceberg tables by using the fully qualified table name, including the Spark session catalog name, as follows:

  ```
  <catalog_name>.<database_name>.<table_name>
  ```

  Alternatively, you can change the default catalog to the Iceberg catalog that you defined by setting `spark.sql.defaultCatalog` to your catalog name. You can use this second approach to refer to tables without the catalog prefix, which can simplify your queries.
- `<catalog_name>.<warehouse>` points to the Amazon S3 path where you want to store your data and metadata.
- To make the catalog an AWS Glue Data Catalog, set `spark.sql.catalog.<catalog_name>.type` to `glue`. This key is required to point to an implementation class for any custom catalog implementation. For catalogs supported by Iceberg, see the General best practices section later in this guide.

For example, if you have a catalog called `glue_iceberg`, you can configure your job by using multiple `--conf` keys as follows:

```
%%configure
```

```
{
  "--datalake-formats" : "iceberg",
  "--conf" :
 "spark.sql.extensions=org.apache.iceberg.spark.extensions.IcebergSparkSessionExtensions
 --conf spark.sql.catalog.glue_iceberg=org.apache.iceberg.spark.SparkCatalog --
conf spark.sql.catalog.glue_iceberg.warehouse=s3://<your-warehouse-dir>/ --conf
 spark.sql.catalog.glue_iceberg.type=glue"
}
```

Alternatively, you can use code to add the above configurations to your Spark script as follows:

```
spark = SparkSession.builder\

 .config("spark.sql.extensions","org.apache.iceberg.spark.extensions.IcebergSparkSessionExtensi
                    .config("spark.sql.catalog.glue_iceberg",
 "org.apache.iceberg.spark.SparkCatalog")\
                    .config("spark.sql.catalog.glue_iceberg.warehouse","s3://<your-
warehouse-dir>/")\
                    .config("spark.sql.catalog.glue_iceberg.type", "glue") \
                    .getOrCreate()
```

Best practices for AWS Glue jobs

This section provides general guidelines for tuning Spark jobs in AWS Glue to optimize reading and writing data to Iceberg tables. For Iceberg-specific best practices, see the Best practices section later in this guide.

- **Use the latest version of AWS Glue and upgrade whenever possible** – New versions of AWS Glue provide performance improvements, reduced startup times, and new features. They also support newer Spark versions that might be required for the latest Iceberg versions. For a list of available AWS Glue versions and the Spark versions they support, see the AWS Glue documentation.
- **Optimize AWS Glue job memory** – Follow the recommendations in the AWS blog post Optimize memory management in AWS Glue.
- **Use AWS Glue Auto Scaling** – When you enable Auto Scaling, AWS Glue automatically adjusts the number of AWS Glue workers dynamically based on your workload. This helps reduce the cost of your AWS Glue job during peak loads, because AWS Glue scales down the number of workers when the workload is small and workers are sitting idle. To use AWS Glue Auto Scaling,

you specify a maximum number of workers that your AWS Glue job can scale to. For more information, see Using auto scaling for AWS Glue in the AWS Glue documentation.

- **Use the desired Iceberg version –** AWS Glue native integration for Iceberg is best for getting started with Iceberg. However, for production workloads, we recommend that you add library dependencies (as discussed earlier in this guide) to get full control over the Iceberg version. This approach helps you benefit from the latest Iceberg features and performance improvements in your AWS Glue jobs.
- **Enable the Spark UI for monitoring and debugging –** You can also use the Spark UI in AWS Glue to inspect your Iceberg job by visualizing the different stages of a Spark job in a directed acyclic graph (DAG) and monitoring the jobs in detail. Spark UI provides an effective way to both troubleshoot and optimize Iceberg jobs. For example, you can identify bottleneck stages that have large shuffles or disk spill to identify tuning opportunities. For more information, see Monitoring jobs using the Apache Spark web UI in the AWS Glue documentation.

Working with Iceberg tables by using Apache Spark

This section provides an overview of using Apache Spark to interact with Iceberg tables. The examples are boilerplate code that can run on Amazon EMR or AWS Glue.

Note: The primary interface for interacting with Iceberg tables is SQL, so most of the examples will combine Spark SQL with the DataFrames API.

Creating and writing Iceberg tables

You can use Spark SQL and Spark DataFrames to create and add data to Iceberg tables.

Using Spark SQL

To write an Iceberg dataset, use standard Spark SQL statements such as `CREATE TABLE` and `INSERT INTO`.

Unpartitioned tables

Here's an example of creating an unpartitioned Iceberg table with Spark SQL:

```
spark.sql(f"""
    CREATE TABLE IF NOT EXISTS {CATALOG_NAME}.{DB_NAME}.{TABLE_NAME}_nopartitions (
        c_customer_sk             int,
        c_customer_id             string,
        c_first_name              string,
        c_last_name               string,
        c_birth_country           string,
        c_email_address           string)
    USING iceberg
    OPTIONS ('format-version'='2')
""")
```

To insert data into an unpartitioned table, use a standard `INSERT INTO` statement:

```
spark.sql(f"""
INSERT INTO {CATALOG_NAME}.{DB_NAME}.{TABLE_NAME}_nopartitions
SELECT c_customer_sk, c_customer_id, c_first_name, c_last_name, c_birth_country,
 c_email_address
FROM another_table
""")
```

Partitioned tables

Here's an example of creating a partitioned Iceberg table with Spark SQL:

```
spark.sql(f"""
    CREATE TABLE IF NOT EXISTS {CATALOG_NAME}.{DB_NAME}.{TABLE_NAME}_withpartitions (
        c_customer_sk             int,
        c_customer_id             string,
        c_first_name              string,
        c_last_name               string,
        c_birth_country           string,
        c_email_address           string)
    USING iceberg
    PARTITIONED BY (c_birth_country)
    OPTIONS ('format-version'='2')
""")
```

To insert data into a partitioned Iceberg table with Spark SQL, use a standard `INSERT INTO` statement:

```
spark.sql(f"""
INSERT INTO {CATALOG_NAME}.{DB_NAME}.{TABLE_NAME}_withpartitions
SELECT c_customer_sk, c_customer_id, c_first_name, c_last_name, c_birth_country,
 c_email_address
FROM another_table
""")
```

Note

Starting with Iceberg 1.5.0, `hash` write distribution mode is the default when you insert data into partitioned tables. For more information, see Writing Distribution Modes in the Iceberg documentation.

Using the DataFrames API

To write an Iceberg dataset, you can use the `DataFrameWriterV2` API.

To create an Iceberg table and write data to it, use the `df.writeTo(t)` function. If the table exists, use the `.append()` function. If it doesn't, use `.create().` The following examples use `.createOrReplace()`, which is a variation of `.create()` that's equivalent to `CREATE OR REPLACE TABLE AS SELECT`.

Unpartitioned tables

To create and populate an unpartitioned Iceberg table by using the `DataFrameWriterV2` API:

```
input_data.writeTo(f"{CATALOG_NAME}.{DB_NAME}.{TABLE_NAME}_nopartitions") \
    .tableProperty("format-version", "2") \
    .createOrReplace()
```

To insert data into an existing unpartitioned Iceberg table by using the `DataFrameWriterV2` API:

```
input_data.writeTo(f"{CATALOG_NAME}.{DB_NAME}.{TABLE_NAME}_nopartitions") \
    .append()
```

Partitioned tables

To create and populate a partitioned Iceberg table by using the `DataFrameWriterV2` API:

```
input_data.writeTo(f"{CATALOG_NAME}.{DB_NAME}.{TABLE_NAME}_withpartitions") \
    .tableProperty("format-version", "2") \
    .partitionedBy("c_birth_country") \
    .createOrReplace()
```

To insert data into a partitioned Iceberg table by using the `DataFrameWriterV2` API:

```
input_data.writeTo(f"{CATALOG_NAME}.{DB_NAME}.{TABLE_NAME}_withpartitions") \
    .append()
```

Updating data in Iceberg tables

The following example shows how to update data in an Iceberg table. This example modifies all rows that have an even number in the `c_customer_sk` column.

```
spark.sql(f"""
UPDATE {CATALOG_NAME}.{db.name}.{table.name}
SET c_email_address = 'even_row'
WHERE c_customer_sk % 2 == 0
""")
```

This operation uses the default copy-on-write strategy, so it rewrites all impacted data files.

Upserting data in Iceberg tables

Upserting data refers to inserting new data records and updating existing data records in a single transaction. To upsert data into an Iceberg table, you use the `SQL MERGE INTO` statement.

The following example upserts the content of the table `{UPSERT_TABLE_NAME}` inside the table `{TABLE_NAME}`:

```
spark.sql(f"""
    MERGE INTO {CATALOG_NAME}.{DB_NAME}.{TABLE_NAME} t
    USING {UPSERT_TABLE_NAME} s
        ON t.c_customer_id = s.c_customer_id
    WHEN MATCHED THEN UPDATE SET t.c_email_address = s.c_email_address
    WHEN NOT MATCHED THEN INSERT *
""")
```

- If a customer record that's in `{UPSERT_TABLE_NAME}` already exists in `{TABLE_NAME}` with the same `c_customer_id`, the `{UPSERT_TABLE_NAME}` record `c_email_address` value overrides the existing value (update operation).
- If a customer record that's in `{UPSERT_TABLE_NAME}` doesn't exist in `{TABLE_NAME}`, the `{UPSERT_TABLE_NAME}` record is added to `{TABLE_NAME}` (insert operation).

Deleting data in Iceberg tables

To delete data from an Iceberg table, use the `DELETE FROM` expression and specify a filter that matches the rows to delete.

```
spark.sql(f"""
DELETE FROM {CATALOG_NAME}.{db.name}.{table.name}
WHERE c_customer_sk % 2 != 0
""")
```

If the filter matches an entire partition, Iceberg performs a metadata-only delete and leaves the data files in place. Otherwise, it rewrites only the affected data files.

The delete method takes the data files that are impacted by the `WHERE` clause and creates a copy of them without the deleted records. It then creates a new table snapshot that points to the new data files. Therefore, the deleted records are still present in the older snapshots of the table. For example, if you retrieve the previous snapshot of the table, you'll see the data that you just deleted. For information about removing unneeded old snapshots with the related data files for cleanup purposes, see the section Maintaining files by using compaction later in this guide.

Reading data

You can read the latest status of your Iceberg tables in Spark with both Spark SQL and DataFrames.

Example using Spark SQL:

```
spark.sql(f"""
SELECT * FROM {CATALOG_NAME}.{db.name}.{table.name} LIMIT 5
""")
```

Example using the DataFrames API:

```
df = spark.table(f"{CATALOG_NAME}.{DB_NAME}.{TABLE_NAME}").limit(5)
```

Using time travel

Each write operation (insert, update, upsert, delete) in an Iceberg table creates a new snapshot. You can then use these snapshots for time travel—to go back in time and check the status of a table in the past.

For information about how to retrieve the history of snapshots for tables by using `snapshot-id` and timing values, see the Accessing metadata section later in this guide.

The following time travel query displays the status of a table based on a specific `snapshot-id`.

Using Spark SQL:

```
spark.sql(f"""
SELECT * FROM {CATALOG_NAME}.{DB_NAME}.{TABLE_NAME} VERSION AS OF {snapshot_id}
""")
```

Using the DataFrames API:

```
df_1st_snapshot_id = spark.read.option("snapshot-id", snapshot_id) \
     .format("iceberg") \
     .load(f"{CATALOG_NAME}.{DB_NAME}.{TABLE_NAME}") \
     .limit(5)
```

The following time travel query displays the status of a table based on the last snapshot that was created before a specific timestamp, in milliseconds (`as-of-timestamp`).

Using Spark SQL:

```
spark.sql(f"""
SELECT * FROM dev.{db.name}.{table.name} TIMESTAMP AS OF '{snapshot_ts}'
""")
```

Using the DataFrames API:

```
df_1st_snapshot_ts = spark.read.option("as-of-timestamp", snapshot_ts) \
                          .format("iceberg") \
                          .load(f"dev.{DB_NAME}.{TABLE_NAME}") \
                          .limit(5)
```

Using incremental queries

You can also use Iceberg snapshots to read appended data incrementally.

Note: Currently, this operation supports reading data from `append` snapshots. It doesn't support fetching data from operations such as `replace`, `overwrite`, or `delete`. Additionally, incremental read operations aren't supported in the Spark SQL syntax.

The following example retrieves all the records appended to an Iceberg table between the snapshot `start-snapshot-id` (exclusive) and `end-snapshot-id` (inclusive).

```
df_incremental = (spark.read.format("iceberg")
    .option("start-snapshot-id", snapshot_id_start)
    .option("end-snapshot-id", snapshot_id_end)
    .load(f"glue_catalog.{DB_NAME}.{TABLE_NAME}")
)
```

Accessing metadata

Iceberg provides access to its metadata through SQL. You can access the metadata for any given table (`<table_name>`) by querying the namespace `<table_name>.<metadata_table>`. For a complete list of metadata tables, see Inspecting tables in the Iceberg documentation.

The following example shows how to access the Iceberg history metadata table, which shows the history of commits (changes) for an Iceberg table.

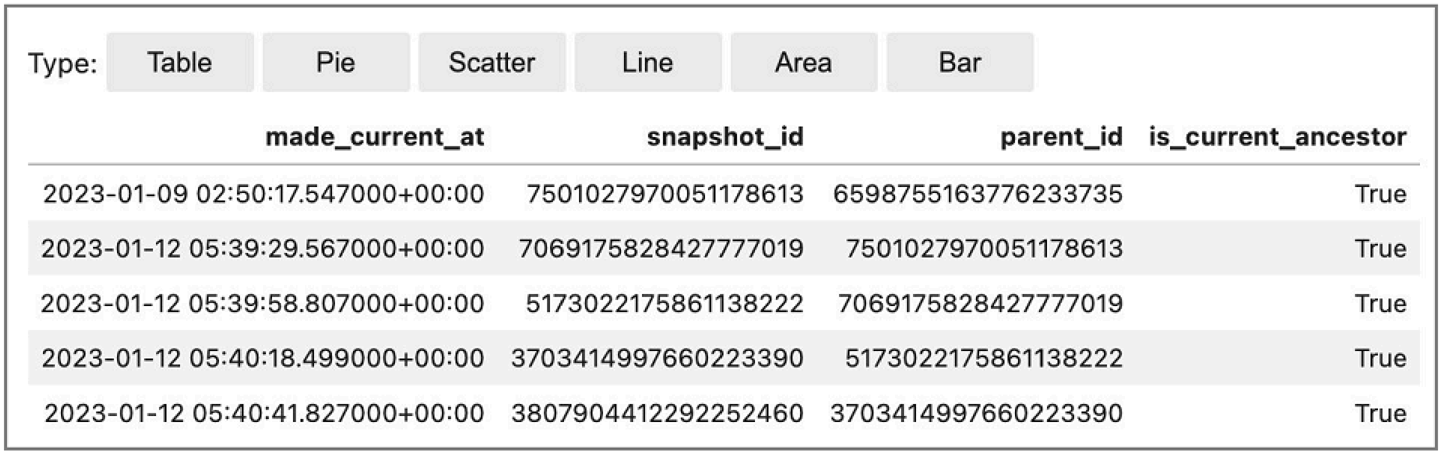
Using Spark SQL (with the `%%sql` magic) from an Amazon EMR Studio notebook:

```
Spark.sql(f"""
SELECT * FROM {CATALOG_NAME}.{DB_NAME}.{TABLE_NAME}.history LIMIT 5
""")
```

Using the DataFrames API:

```
spark.read.format("iceberg").load("{CATALOG_NAME}.{DB_NAME}.
{TABLE_NAME}.history").show(5,False)
```

Sample output:



made_current_at	snapshot_id	parent_id	is_current_ancestor
2023-01-09 02:50:17.547000+00:00	7501027970051178613	6598755163776233735	True
2023-01-12 05:39:29.567000+00:00	7069175828427777019	7501027970051178613	True
2023-01-12 05:39:58.807000+00:00	5173022175861138222	7069175828427777019	True
2023-01-12 05:40:18.499000+00:00	3703414997660223390	5173022175861138222	True
2023-01-12 05:40:41.827000+00:00	3807904412292252460	3703414997660223390	True

Working with Iceberg tables by using Trino

This section describes how to set up and operate Iceberg tables by using Trino on Amazon EMR. The examples are boilerplate code that you can run on an Amazon EMR on EC2 cluster. The code examples and configurations in this section assume that you're using Amazon EMR release **emr-7.9.0**.

Amazon EMR on EC2 setup

1. Create an `iceberg.properties` file with the following content. The `iceberg.file-format=parquet` setting determines the default storage format for new tables if the format isn't explicitly specified in the `CREATE TABLE` statement.

```
connector.name=iceberg
iceberg.catalog.type=glue
iceberg.file-format=parquet
fs.native-s3.enabled=true
```

2. Upload the `iceberg.properties` file to your S3 bucket.
3. Create a bootstrap action that copies the `iceberg.properties` file from your S3 bucket and stores it as a Trino configuration file on the Amazon EMR cluster that you will be creating. Make sure to replace `<S3-bucket-name>` with your S3 bucket name.

```
#!/bin/bash
set -ex
sudo aws s3 cp s3://<S3-bucket-name>/iceberg.properties /etc/trino/conf/catalog/
iceberg.properties
```

4. Create an Amazon EMR cluster with Trino installed and specify the execution of the previous script as a bootstrap action. Here's a sample AWS Command Line Interface (AWS CLI) command for creating the cluster:

```
aws emr create-cluster --release-label emr-7.9.0 \
--applications Name=Trino \
--region <region> \
--name Trino_Iceberg_Cluster \
--bootstrap-actions '[{"Path":"s3://<S3-bucket-name>/bootstrap.sh","Name":"Add
 iceberg.properties"}]' \
--instance-groups
 '[{"InstanceGroupType":"MASTER","InstanceCount":1,"InstanceType":"m5.xlarge"},
{"InstanceGroupType":"CORE","InstanceCount":3,"InstanceType":"m5.xlarge"}]' \
--service-role "<IAM-service-role>" \
--ec2-attributes '{"KeyName":"<key-name>","InstanceProfile":"<EMR-EC2-instance-
profile>"}'
```

where you replace:

- `<S3-bucket-name>` with your S3 bucket name
- `<region>` with your specific AWS Region
- `<key-name>` with your key pair. If the key pair doesn't exist, it will be created.
- `<IAM-service-role>` with your Amazon EMR service role that follows the principle of least privilege.
- `<EMR-EC2-instance-profile>` with your instance profile.

5. When the Amazon EMR cluster has been initialized, you can initialize a Trino session by running the following command:

```
trino-cli
```

6. In the Trino CLI, you can view the catalogs by running:

```
SHOW CATALOGS;
```

Creating Iceberg tables

To create an Iceberg table, you can use the `CREATE TABLE` statement. Here's an example of creating a partitioned table that uses Iceberg hidden partitioning:

```
CREATE TABLE iceberg.iceberg_db.iceberg_table (
             userid int,
             firstname varchar,
             city varchar)
        WITH (
             format = 'PARQUET',
             partitioning = ARRAY['city', 'bucket(userid, 16)'],
             location = 's3://<S3-bucket>/<prefix>');
```

Note

If you don't specify the format, the `iceberg.file-format` value that you configured in the previous section will be used.

To insert data, use the `INSERT INTO` command. Here's an example:

```
INSERT INTO iceberg.iceberg_db.iceberg_table (userid, firstname, city)
VALUES
    (1001, 'John', 'New York'),
    (1002, 'Mary', 'Los Angeles'),
    (1003, 'Mateo', 'Chicago'),
    (1004, 'Shirley', 'Houston'),
    (1005, 'Diego', 'Miami'),
    (1006, 'Nikki', 'Seattle'),
    (1007, 'Pat', 'Boston'),
    (1008, 'Terry', 'San Francisco'),
    (1009, 'Richard', 'Denver'),
    (1010, 'Pat', 'Phoenix');
```

Reading from Iceberg tables

You can read the latest status of your Iceberg table by using a `SELECT` statement, as follows:

```
SELECT * FROM iceberg.iceberg_db.iceberg_table;
```

Upserting data into Iceberg tables

You can perform an upsert operation (simultaneously insert new records and update existing ones) by using the `MERGE INTO` statement. Here's an example:

```
MERGE INTO iceberg.iceberg_db.iceberg_table target
USING (
      VALUES
        (1001, 'John Updated', 'Boston'),       -- Update existing user
        (1002, 'Mary Updated', 'Seattle'),      -- Update existing user
        (1011, 'Martha', 'Portland'),           -- Insert new user
        (1012, 'Paulo', 'Austin')               -- Insert new user
```

```
    ) AS source (userid, firstname, city)
   ON target.userid = source.userid
 WHEN MATCHED THEN
      UPDATE SET
        firstname = source.firstname,
        city = source.city
 WHEN NOT MATCHED THEN
      INSERT (userid, firstname, city)
      VALUES (source.userid, source.firstname, source.city);
```

Deleting records from Iceberg tables

To delete data from an Iceberg table, use the `DELETE FROM` expression and specify a filter that matches the rows to delete. Here's an example:

```
DELETE FROM iceberg.iceberg_db.iceberg_table WHERE userid IN (1003, 1004);
```

Querying Iceberg table metadata

Iceberg provides access to its metadata through SQL. You can access the metadata for any given table (`<table_name>`) by querying the namespace `"<table_name>.$<metadata_table>"`. For a complete list of metadata tables, see Inspecting tables in the Iceberg documentation.

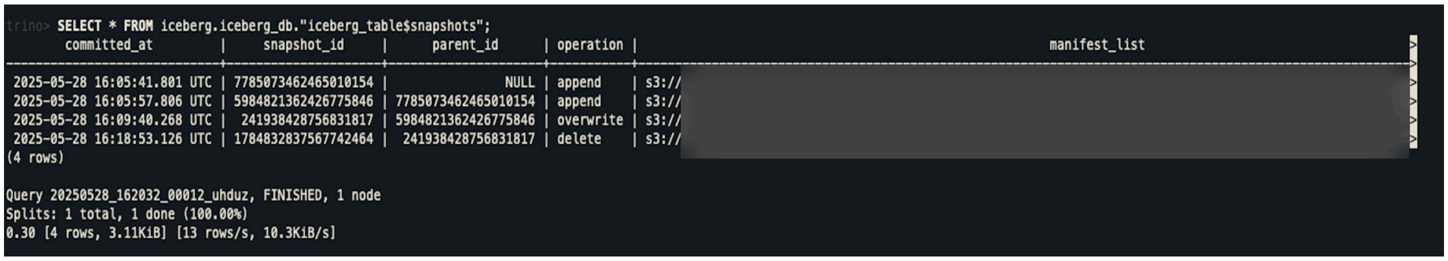
Here's an example list of queries to inspect Iceberg metadata:

```
SELECT  FROM iceberg.iceberg_db."iceberg_table$snapshots";
SELECT  FROM iceberg.iceberg_db."iceberg_table$history";
SELECT  FROM iceberg.iceberg_db."iceberg_table$partitions";
SELECT  FROM iceberg.iceberg_db."iceberg_table$files";
SELECT  FROM iceberg.iceberg_db."iceberg_table$manifests";
SELECT  FROM iceberg.iceberg_db."iceberg_table$refs";
SELECT * FROM iceberg.iceberg_db."iceberg_table$metadata_log_entries";
```

For example, this query:

```
 SELECT * FROM iceberg.iceberg_db."iceberg_table$snapshots";
```

provides the output:



```
trino> SELECT * FROM iceberg.iceberg_db."iceberg_table$snapshots";
       committed_at         |     snapshot_id     |      parent_id      | operation |                              manifest_list
----------------------------+---------------------+---------------------+-----------+------------------------------------------------------------
 2025-05-28 16:05:41.801 UTC | 7785073462465010154 |                NULL | append    | s3://[redacted]
 2025-05-28 16:05:57.806 UTC | 5984821362426775846 | 7785073462465010154 | append    | s3://
 2025-05-28 16:09:40.268 UTC |  241938428756831817 | 5984821362426775846 | overwrite | s3://
 2025-05-28 16:18:53.126 UTC | 1784832837567742464 |  241938428756831817 | delete    | s3://
(4 rows)

Query 20250528_162032_00012_uhduz, FINISHED, 1 node
Splits: 1 total, 1 done (100.00%)
0.30 [4 rows, 3.11KiB] [13 rows/s, 10.3KiB/s]
```

Using time travel

Each write operation (insert, update, upsert, or delete) in an Iceberg table creates a new snapshot. You can then use these snapshots for time travel—to go back in time and check the status of a table in the past.

The following time travel query displays the status of a table based on a specific `snapshot_id`:

```
SELECT *
FROM iceberg.iceberg_db.iceberg_table FOR VERSION AS OF 241938428756831817;
```

The following time travel query displays the status of a table based on a specific timestamp:

```
SELECT *
FROM iceberg.iceberg_db.iceberg_table FOR TIMESTAMP AS OF TIMESTAMP '2025-05-28
 16:09:40.268 UTC'
```

Considerations when using Iceberg with Trino

Trino write operations on Iceberg tables follow the merge-on-read design, so they create positional delete files instead of rewriting entire data files that are impacted by updates or deletes. If you want to use the copy-on-write approach, consider using Spark for write operations.

Working with Iceberg tables by using Amazon Data Firehose

Amazon Data Firehose is a serverless, no-code service for delivering data streams from over 20 sources such as AWS WAF logs, Amazon CloudWatch Logs, AWS IoT, Amazon Kinesis Data Streams, and Amazon Managed Streaming for Apache Kafka (Amazon MSK) into destinations such as Amazon S3, Amazon Redshift, Snowflake, and Splunk.

You can use Firehose to directly deliver streaming data to Apache Iceberg tables in Amazon S3. Using Firehose, you can route records from a single stream into different Apache Iceberg tables, and automatically apply insert, update, and delete operations to records in the tables. Firehose guarantees exactly-once delivery to Iceberg tables. This feature requires using the AWS Glue Data Catalog.

Firehose can also directly deliver streaming data to Amazon S3 tables. These tables provide storage that is optimized for large-scale analytics workloads, and include features that continuously improve query performance and reduce storage costs for tabular data.

For information about how to set up a Firehose stream to deliver data to Apache Iceberg tables, see Set up the Firehose stream in the Firehose documentation or the blog post Stream real-time data into Apache Iceberg tables in Amazon S3 using Amazon Data Firehose.

Working with Iceberg tables by using Athena SQL

Amazon Athena provides built-in support for Apache Iceberg, and doesn't require additional steps or configuration. This section provides a detailed overview of supported features and high-level guidance for using Athena to interact with Iceberg tables.

Version and feature compatibility

Iceberg table specification support

The Apache Iceberg table specification specifies how Iceberg tables should behave. Athena supports table format version 2, so any Iceberg table that you create with the console, CLI, or SDK inherently uses that version.

If you use an Iceberg table that was created with another engine, such as Apache Spark on Amazon EMR or AWS Glue, make sure to set the table format version by using table properties. As a reference, see the section Creating and writing Iceberg tables earlier in this guide.

Iceberg feature support

You can use Athena to read from and write to Iceberg tables. When you change data by using the `UPDATE`, `MERGE INTO`, and `DELETE FROM` statements, Athena supports merge-on-read mode only. This property cannot be changed. In order to update or delete data with copy-on-write, you have to use other engines such as Apache Spark on Amazon EMR or AWS Glue. The following table summarizes Iceberg feature support in Athena.

		DDL support		**DML support**		**AWS Lake Formation for security (optional)**
	Table format	Create table	Schema evolution	Reading data	Writing data	Row/column access control

		DDL support		**DML support**		**AWS Lake Formation for security (optional)**
Amazon Athena	Version 2	✓	✓	✓	X Copy-on-write	✓
					✓ Merge-on-read	✓

Note

- Athena doesn't support incremental queries.
- In Athena, update, delete, and merge operations always default to merge on read (MoR), regardless of any copy on write (CoW) settings in the table properties, because CoW isn't supported.

Working with Iceberg tables

For a quick start to using Iceberg in Athena, see the section Getting started with Iceberg tables in Athena SQL earlier in this guide.

The following table lists limitations and recommendations.

Scenario	Limitation	Recommendation
Table DDL generation	Iceberg tables created with other engines can have properties that are not exposed in Athena. For these tables, it's not possible to generate the DDL.	Use the equivalent statement in the engine that created the table (for example, the `SHOW CREATE TABLE` statement for Spark).

Scenario	Limitation	Recommendation
Random Amazon S3 prefixes in objects that are written to an Iceberg table	By default, Iceberg tables that are created with Athena have the `write.object-storage.enabled` property enabled.	To disable this behavior and gain full control over Iceberg table properties, create an Iceberg table with another engine such as Spark on Amazon EMR or AWS Glue.
Incremental queries	Not currently supported in Athena.	To use incremental queries to enable incremental data ingestion pipelines, use Spark on Amazon EMR or AWS Glue.

Working with Iceberg tables by using PyIceberg

This section explains how you can interact with Iceberg tables by using PyIceberg. The examples provided are boilerplate code that you can run on Amazon Linux 2023 EC2 instances, AWS Lambda functions, or any Python environment with properly configured AWS credentials.

Prerequisites

Note

These examples use PyIceberg 1.9.1.

To work with PyIceberg, you need PyIceberg and AWS SDK for Python (Boto3) installed. Here's an example of how you can set up a Python virtual environment to work with PyIceberg and AWS Glue Data Catalog:

1. Download PyIceberg by using the pip python package installer. You also need Boto3 to interact with AWS services. You can configure a local Python virtual environment to test by using these commands:

```
python3 -m venv my_env
cd my_env/bin/
source activate
pip install "pyiceberg[pyarrow,pandas,glue]"
pip install boto3
```

2. Run `python` to open the Python shell and test the commands.

Connecting to the Data Catalog

To start working with Iceberg tables in AWS Glue, you first need to connect to the AWS Glue Data Catalog.

The `load_catalog` function initializes a connection to the Data Catalog by creating a catalog object that serves as your primary interface for all Iceberg operations:

```
from pyiceberg.catalog import load_catalog
```

```
region = "us-east-1"

glue_catalog = load_catalog(
    'default',
    **{
        'client.region': region
    },
    type='glue'
)
```

Listing and creating databases

To list existing databases, use the `list_namespaces` function:

```
databases = glue_catalog.list_namespaces()
print(databases)
```

To create a new database, use the `create_namespace` function:

```
database_name="mydb"
s3_db_path=f"s3://amzn-s3-demo-bucket/{database_name}"

glue_catalog.create_namespace(database_name, properties={"location": s3_db_path})
```

Creating and writing Iceberg tables

Unpartitioned tables

Here's an example of creating an unpartitioned Iceberg table by using the `create_table` function:

```
from pyiceberg.schema import Schema
from pyiceberg.types import NestedField, StringType, DoubleType

database_name="mydb"
table_name="pyiceberg_table"
s3_table_path=f"s3://amzn-s3-demo-bucket/{database_name}/{table_name}"

schema = Schema(
    NestedField(1, "city", StringType(), required=False),
    NestedField(2, "lat", DoubleType(), required=False),
    NestedField(3, "long", DoubleType(), required=False),
)

glue_catalog.create_table(f"{database_name}.{table_name}", schema=schema,
 location=s3_table_path)
```

You can use the `list_tables` function to check the list of tables inside a database:

```
tables = glue_catalog.list_tables(namespace=database_name)
print(tables)
```

You can use the append function and PyArrow to insert data inside an Iceberg table:

```
import pyarrow as pa
df = pa.Table.from_pylist(
    [
        {"city": "Amsterdam", "lat": 52.371807, "long": 4.896029},
        {"city": "San Francisco", "lat": 37.773972, "long": -122.431297},
        {"city": "Drachten", "lat": 53.11254, "long": 6.0989},
        {"city": "Paris", "lat": 48.864716, "long": 2.349014},
    ],
)

table = glue_catalog.load_table(f"{database_name}.{table_name}")
table.append(df)
```

Partitioned tables

Here's an example of creating a partitioned Iceberg table with hidden partitioning by using the `create_table` function and `PartitionSpec`:

```
from pyiceberg.schema import Schema
from pyiceberg.types import (
    NestedField,
    StringType,
    FloatType,
    DoubleType,
    TimestampType,
)
```

```
# Define the schema
schema = Schema(
    NestedField(field_id=1, name="datetime", field_type=TimestampType(),
 required=True),
    NestedField(field_id=2, name="drone_id", field_type=StringType(), required=True),
    NestedField(field_id=3, name="lat", field_type=DoubleType(), required=False),
    NestedField(field_id=4, name="lon", field_type=DoubleType(), required=False),
    NestedField(field_id=5, name="height", field_type=FloatType(), required=False),
)

from pyiceberg.partitioning import PartitionSpec, PartitionField
from pyiceberg.transforms import DayTransform

partition_spec = PartitionSpec(
    PartitionField(
        source_id=1,  # Refers to "datetime"
        field_id=1000,
        transform=DayTransform(),
        name="datetime_day"
    )
)

database_name="mydb"
partitioned_table_name="pyiceberg_table_partitioned"
s3_table_path=f"s3://amzn-s3-demo-bucket/{database_name}/{partitioned_table_name}"

glue_catalog.create_table(
    identifier=f"{database_name}.{partitioned_table_name}",
    schema=schema,
    location=s3_table_path,
    partition_spec=partition_spec
)
```

You can insert data into a partitioned table the same way as for an unpartitioned table. The partitioning is handled automatically.

```
from datetime import datetime
arrow_schema = pa.schema([
    pa.field("datetime", pa.timestamp("us"), nullable=False),
    pa.field("drone_id", pa.string(), nullable=False),
    pa.field("lat", pa.float64()),
    pa.field("lon", pa.float64()),
    pa.field("height", pa.float32()),
])

data = [
    {
        "datetime": datetime(2024, 6, 1, 12, 0, 0),
        "drone_id": "drone_001",
        "lat": 52.371807,
        "lon": 4.896029,
        "height": 120.5,
    },
    {
        "datetime": datetime(2024, 6, 1, 12, 5, 0),
        "drone_id": "drone_002",
        "lat": 37.773972,
        "lon": -122.431297,
        "height": 150.0,
    },
    {
        "datetime": datetime(2024, 6, 2, 9, 0, 0),
        "drone_id": "drone_001",
        "lat": 53.11254,
        "lon": 6.0989,
        "height": 110.2,
    },
    {
        "datetime": datetime(2024, 6, 2, 9, 30, 0),
        "drone_id": "drone_003",
        "lat": 48.864716,
        "lon": 2.349014,
        "height": 145.7,
    },
]

df = pa.Table.from_pylist(data, schema=arrow_schema)

table = glue_catalog.load_table(f"{database_name}.{partitioned_table_name}")
table.append(df)
```

Reading data

You can use the PyIceberg `scan` function to read data from your Iceberg tables. You can filter rows, select specific columns, and limit the number of returned records.

```
table= glue_catalog.load_table(f"{database_name}.{table_name}")
scan_df = table.scan(
    row_filter=(
        f"city = 'Amsterdam'"
    ),
    selected_fields=("city", "lat"),
    limit=100,
).to_pandas()

print(scan_df)
```

Deleting data

The PyIceberg `delete` function lets you remove records from your table by using a `delete_filter`:

```
table = glue_catalog.load_table(f"{database_name}.{table_name}")
table.delete(delete_filter="city == 'Paris'")
```

Accessing metadata

PyIceberg provides several functions to access table metadata. Here's how you can view information about table snapshots:

```
#List of snapshots
table.snapshots()

#Current snapshot
table.current_snapshot()

#Take a previous snapshot
second_last_snapshot_id=table.snapshots()[-2].snapshot_id
print(f"Second last SnapshotID: {second_last_snapshot_id}")
```

For a detailed list of available metadata, see the metadata code reference section of the PyIceberg documentation.

Using time travel

You can use table snapshots for time travel to access previous states of your table. Here's how to view the table state before the last operation:

```
second_last_snapshot_id=table.snapshots()[-2].snapshot_id

time_travel_df = table.scan(
    limit=100,
    snapshot_id=second_last_snapshot_id
).to_pandas()

print(time_travel_df)
```

For a complete list of available functions, see the PyIceberg Python API documentation.

Working with Iceberg table format specification version 3

The latest version of the Apache Iceberg table format specification is version 3. This version introduces advanced capabilities for building petabyte-scale data lakes with improved performance and reduced operational overhead. It addresses common performance bottlenecks encountered with version 2, particularly around batch updates and compliance delete operations.

AWS provides support for deletion vectors and row lineage as defined in the Iceberg version 3 specification. These features are available with Apache Spark on the following AWS services.

AWS service	Version 3 support
Amazon EMR for Apache Spark	Amazon EMR release 7.12 and later
AWS Glue	Yes
AWS Glue: Iceberg REST API, table maintenance	Yes
Amazon SageMaker Unified Studio notebooks	Yes
Amazon S3 Tables: Iceberg REST API, table maintenance	Yes
Amazon Athena (Trino)	No

Key features in version 3

Deletion vectors replace the positional delete files that were used in version 2 with an efficient binary format stored as Puffin files. This eliminates write amplification from random batch updates and General Data Protection Regulation (GDPR) compliance deletes, and significantly reduces the overhead of maintaining fresh data. Organizations that process high-frequency updates will see immediate improvements in write performance and reduced storage costs from fewer small files.

Row lineage enables precise change tracking at the row level. Your downstream systems can process changes incrementally, speeding up data pipelines and reducing compute costs for change data capture (CDC) workflows. This built-in capability eliminates the need for custom change tracking implementations.

Version compatibility

Version 3 maintains backward compatibility with version 2 tables. AWS services support both version 2 and version 3 tables simultaneously, so you can:

- Run queries across both version 2 and version 3 tables.
- Upgrade existing version 2 tables to version 3 without data rewrites.
- Run time travel queries that span version 2 and version 3 snapshots.
- Use schema evolution and hidden partitioning across table versions.

Getting started with version 3

Prerequisites

Before working with version 3 tables, make sure that you have:

- An AWS account with appropriate AWS Identity and Access Management (IAM) permissions.
- Access to one or more AWS analytics services (Amazon EMR, AWS Glue, Amazon SageMaker Unified Studio notebooks, or Amazon S3 Tables).
- An S3 bucket for storing table data and metadata.
- A table bucket to get started with Amazon S3 Tables or a general-purpose S3 bucket if you are building your own Iceberg infrastructure.
- A configured AWS Glue catalog.

Creating version 3 tables

Creating new tables

To create a new Iceberg version 3 table, set the `format-version` table property to 3.

Using Spark SQL:

```
CREATE TABLE IF NOT EXISTS myns.orders_v3 (
    order_id bigint,
    customer_id string,
    order_date date,
    total_amount decimal(10,2),
    status string,
    created_at timestamp
)
USING iceberg
TBLPROPERTIES (
    'format-version' = '3'
)
```

Upgrading version 2 tables to version 3

You can upgrade existing version 2 tables to version 3 atomically without rewriting data.

Using Spark SQL:

```
ALTER TABLE myns.existing_table
SET TBLPROPERTIES ('format-version' = '3')
```

Important

Version 3 is a one-way upgrade. After a table is upgraded from version 2 to version 3, it cannot be downgraded back to version 2 through standard operations.

What happens during upgrade:

- A new metadata snapshot is created atomically.
- Existing Parquet data files are reused.
- Row lineage fields are added to the table metadata.

After the upgrade:

- The next compaction will remove old version 2 delete files.
- New modifications will use the version 3 deletion vector files.

The upgrade doesn't perform a historical backfill of row lineage change tracking records.

Enabling deletion vectors

To take advantage of deletion vectors for updates, deletes, and merges, configure your write mode.

Using Spark SQL:

```
ALTER TABLE myns.orders_v3
SET TBLPROPERTIES ('format-version' = '3',
                   'write.delete.mode' = 'merge-on-read',
                   'write.update.mode' = 'merge-on-read',
                   'write.merge.mode' = 'merge-on-read'
                  )
```

These settings ensure that update, delete, and merge operations create deletion vector files instead of rewriting entire data files.

Using row lineage for change tracking

Version 3 automatically adds row lineage metadata fields to track changes.

Using Spark SQL:

```
# Query with parameter value provided
last_processed_sequence = 47

SELECT
    id,
    data,
    _row_id,
    _last_updated_sequence_number
FROM myns.orders_v3
WHERE _last_updated_sequence_number > :last_processed_sequence
```

The `_row_id` field uniquely identifies each row, and `_last_updated_sequence_number` tracks when the row was last modified. Use these fields to:

- Identify changed rows for incremental processing.
- Track data lineage for compliance.
- Optimize CDC pipelines.

- Reduce compute costs by processing only changes.

Best practices for version 3

When to use version 3

Consider upgrading to, or starting with, version 3 when:

- You perform frequent batch updates or deletes.
- You need to meet GDPR or compliance delete requirements.
- Your workloads involve high-frequency upserts.
- You require efficient CDC workflows.
- You want to reduce storage costs from small files.
- You need better change tracking capabilities.

Optimizing write performance

- Enable deletion vectors for update-heavy workloads:

```
SET TBLPROPERTIES (
'write.delete.mode' = 'merge-on-read',
'write.update.mode' = 'merge-on-read',
'write.merge.mode' = 'merge-on-read'
)
```

- Configure appropriate file sizes:

```
SET TBLPROPERTIES (
'write.target-file-size-bytes' = '536870912'  — 512 MB
)
```

Optimizing read performance

- Use row lineage for incremental processing.
- Use time travel to access historical data without copying.
- Enable statistics collection for better query planning.

Migration strategy

When you migrate from version 2 to version 3, follow these best practices:

- Test in a non-production environment first to validate the upgrade process and performance.
- Upgrade during low-activity periods to minimize impact on concurrent operations.
- Monitor initial performance, and track metrics after the upgrade.
- Run compaction to consolidate delete files after the upgrade.
- Update your team documentation to reflect version 3 features.

Compatibility considerations

- Engine versions – Make sure that all engines accessing the table support version 3.
- Third-party tools – Verify your tool's version 3 compatibility before you upgrade.
- Backup strategy – Test snapshot-based recovery procedures.
- Monitoring – Update monitoring dashboards for version 3-specific metrics.

Troubleshooting

Common issues

Error: "format-version 3 is not supported"

- Verify that your engine version supports version 3. For specifics, see the table at the beginning of this section.
- Check catalog compatibility.
- Make sure that you're using the latest versions of AWS services.

Performance degradation after upgrade

- Verify that there are no compaction compaction failures. For more information, see Logging and monitoring for S3 Tables in the Amazon S3 documentation.
- Confirm that deletion vectors are enabled. The following properties should be set:

```
SET TBLPROPERTIES (
'write.delete.mode' = 'merge-on-read',
'write.update.mode' = 'merge-on-read',
'write.merge.mode' = 'merge-on-read'
)
```

You can verify table properties with the following code:

```
DESCRIBE FORMATTED myns.orders_v3
```

- Review your partition strategy. Over-partitioning can lead to small files. Run the following query to get the average file size for your table:

```
SELECT avg(file_size_in_bytes) as avg_file_size_bytes
FROM myns.orders_v3.files
```

Incompatibility with third-party tools

- Verify that the tool supports the version 3 specification.
- Consider maintaining version 2 tables for unsupported tools.
- Contact the tool vendor for their version 3 support timeline.

Getting help

- For AWS service-specific issues, contact AWS Support.
- To get help from the Iceberg community, use the Iceberg Slack channel.
- For information about using AWS services to manage your analytics workloads, see Analytics on AWS.

Pricing

- Amazon EMR compute and storage pricing
- Amazon SageMaker pricing
- AWS Glue job run and Data Catalog pricing

- S3 Tables storage and requests pricing

Availability

Iceberg table format specification version 3 support is available in all AWS Regions where Amazon EMR, AWS Glue, AWS Glue Data Catalog, and S3 Tables operate. For Region availability, see AWS services by Region.

Additional resources

- Apache Iceberg documentation
- Apache Iceberg table spec
- Guidance for migrating tabular data from Amazon S3 to S3 Tables
- Tutorial: Getting started with S3 Tables

Migrating existing tables to Iceberg

This section focuses on migrating your existing Hive-style tables to Iceberg format. It applies to tables that use traditional Hive-compatible formats such as Apache Parquet or Apache ORC. This information doesn't apply to tables that already use modern table formats such as Linux Foundation Delta Lake or Apache Hudi.

To migrate your current Hive-style tables to Iceberg format, you can use either in-place or full data migration:

- In-place migration is the process of generating Iceberg's metadata files on top of existing data files.
- Full data migration creates the Iceberg metadata layer and also rewrites existing data files from the original table to the new Iceberg table.

The following sections provide a detailed overview of each migration method, including step-by-step instructions and considerations for implementation. For more information about these migration strategies, see the Table Migration section of the Iceberg documentation.

After you review the details of the in-place and full data migration methods, see the following two key sections to aid your decision-making process:

- Choosing a migration strategy provides guidance through a series of questions and scenarios, to help you determine the most suitable migration approach based on your specific requirements and use cases.
- Migration options summary provides a comprehensive table that compares key characteristics and considerations across different migration options. This table serves as a quick reference guide and offers a feature comparison to help you understand the technical trade-offs between methods.

In-place migration

In-place migration eliminates the need to rewrite all your data files. Instead, Iceberg metadata files are generated and linked to your existing data files. This method is typically faster and more cost-effective, especially for large datasets or tables that have compatible file formats such as Parquet, Avro, and ORC.

Note

In-place migration cannot be used when migrating to Amazon S3 Tables.

Iceberg offers two main options for implementing in-place migration:

- Using the snapshot procedure to create a new Iceberg table while keeping the source table unchanged. For more information, see Snapshot Table in the Iceberg documentation.
- Using the migrate procedure to create a new Iceberg table as a substitution for the source table. For more information, see Migrate Table in the Iceberg documentation. Although this procedure works with Hive Metastore (HMS), it isn't currently compatible with the AWS Glue Data Catalog. The Replicating the table migration procedure in AWS Glue Data Catalog section later in this guide provides a workaround for achieving a similar outcome with the Data Catalog.

After you perform in-place migration by using either `snapshot` or `migrate`, some data files might remain unmigrated. This typically happens when writers continue writing to the source table during or after migration. To incorporate these remaining files into your Iceberg table, you can use the add_files procedure. For more information, see Add Files in the Iceberg documentation.

Let's say you have a Parquet-based `products` table that was created and populated in Athena as follows:

```
CREATE EXTERNAL TABLE mydb.products (
    product_id INT,
    product_name STRING
)
PARTITIONED BY (category STRING)
STORED AS PARQUET
LOCATION 's3://amzn-s3-demo-bucket/products/';

INSERT INTO mydb.products
VALUES
    (1001, 'Smartphone', 'electronics'),
    (1002, 'Laptop', 'electronics'),
    (2001, 'T-Shirt', 'clothing'),
    (2002, 'Jeans', 'clothing');
```

The following sections explain how you can use the `snapshot` and `migrate` procedures with this table.

Option 1: snapshot procedure

The `snapshot` procedure creates a new Iceberg table that has a different name but replicates the schema and partitioning of the source table. This operation leaves the source table completely unchanged both during and after the action. It effectively creates a lightweight copy of the table, which is particularly useful for testing scenarios or data exploration without risking modifications to the original data source. This approach enables a transition period where both the original table and the Iceberg table remain available (see the notes at the end of this section). When testing is complete, you can move your new Iceberg table to production by transitioning all writers and readers to the new table.

You can run the `snapshot` procedure by using Spark in any Amazon EMR deployment model (for example, Amazon EMR on EC2, Amazon EMR on EKS, EMR Serverless) and AWS Glue.

To test in-place migration with the `snapshot` Spark procedure, follow these steps:

1. Launch a Spark application and configure the Spark session with the following settings:
   - `"spark.sql.extensions":"org.apache.iceberg.spark.extensions.IcebergSparkSess`
   - `"spark.sql.catalog.spark_catalog":"org.apache.iceberg.spark.SparkSessionCatal`
   - `"spark.sql.catalog.spark_catalog.type":"glue"`
   - `"spark.hadoop.hive.metastore.client.factory.class":"com.amazonaws.glue.catal`
2. Run the `snapshot` procedure to create a new Iceberg table that points to the original table data files:

   ```
   spark.sql(f"""
   CALL system.snapshot(
   source_table => 'mydb.products',
   table => 'mydb.products_iceberg',
   location => 's3://amzn-s3-demo-bucket/products_iceberg/'
   )
   """
   ).show(truncate=False)
   ```

   The output dataframe contains the `imported_files_count` (the numbers of files that were added).

3. Validate the new table by querying it:

```
spark.sql(f"""
SELECT * FROM mydb.products_iceberg LIMIT 10
"""
).show(truncate=False)
```

Notes

- After you run the procedure, any data file modifications on the source table will throw the generated table out of sync. New files that you add won't be visible in the Iceberg table, and files that you removed will affect query capabilities in the Iceberg table. To avoid the synchronization issues:
  - If the new Iceberg table is intended for production use, stop all processes that write to the original table and redirect them to the new table.
  - If you need a transition period or if the new Iceberg table is for testing purposes, see Keeping Iceberg tables in sync after in-place migration later in this section for guidance on maintaining table synchronization.
- When you use the `snapshot` procedure, the `gc.enabled` property is set to `false` in the table properties of the created Iceberg table. This setting prohibits actions such as `expire_snapshots`, `remove_orphan_files`, or `DROP TABLE` with the `PURGE` option, which would physically delete data files. Iceberg delete or merge operations, which do not directly impact source files, are still allowed.
- To make your new Iceberg table fully functional, with no limits on actions that physically delete data files, you can change the `gc.enabled` table property to `true`. However, this setting will allow actions that impact source data files, which could corrupt access to the original table. Therefore, change the `gc.enabled` property only if you no longer need to maintain the original table's functionality. For example:

  ```
  spark.sql(f"""
  ALTER TABLE mydb.products_iceberg
  SET TBLPROPERTIES ('gc.enabled' = 'true');
  """)
  ```

Option 2: migrate procedure

The `migrate` procedure creates a new Iceberg table that has the same name, schema, and partitioning as the source table. When this procedure runs, it locks the source table and renames it to `<table_name>_BACKUP_` (or a custom name specified by the `backup_table_name` procedure parameter).

Note

If you set the `drop_backup` procedure parameter to `true`, the original table will not be retained as a backup.

Consequently, the `migrate` table procedure requires all modifications that affect the source table to be stopped before the action is performed. Before you run the `migrate` procedure:

- Stop all writers that interact with the source table.
- Modify readers and writers that don't natively support Iceberg to enable Iceberg support.

For example:

- Athena continues to work without modification.
- Spark requires:
  - Iceberg Java Archive (JAR) files to be included in the classpath (see the Working with Iceberg in Amazon EMR and Working with Iceberg in AWS Glue sections earlier in this guide).
  - The following Spark session catalog configurations (using `SparkSessionCatalog` to add Iceberg support while maintaining built-in catalog functionalities for non-Iceberg tables):
    - `"spark.sql.extensions":"org.apache.iceberg.spark.extensions.IcebergSparkSes`
    - `"spark.sql.catalog.spark_catalog":"org.apache.iceberg.spark.SparkSessionCat`
    - `"spark.sql.catalog.spark_catalog.type":"glue"`
    - `"spark.hadoop.hive.metastore.client.factory.class":"com.amazonaws.glue.cata`

After you run the procedure, you can restart your writers with their new Iceberg configuration.

Currently, the `migrate` procedure isn't compatible with the AWS Glue Data Catalog, because the Data Catalog doesn't support the `RENAME` operation. Therefore, we recommend that you use this procedure only when you're working with Hive Metastore. If you're using the Data Catalog, see the next section for an alternative approach.

You can run the `migrate` procedure across all Amazon EMR deployment models (Amazon EMR on EC2, Amazon EMR on EKS, EMR Serverless) and AWS Glue, but it requires a configured connection to Hive Metastore. Amazon EMR on EC2 is the recommended choice because it provides a built-in Hive Metastore configuration, which minimizes setup complexity.

To test in-place migration with the `migrate` Spark procedure from an Amazon EMR on EC2 cluster that's configured with Hive Metastore, follow these steps:

1. Launch a Spark application and configure the Spark session to use the Iceberg Hive catalog implementation. For example, if you're using the `pyspark` CLI:

   ```
   pyspark --conf
    spark.sql.extensions=org.apache.iceberg.spark.extensions.IcebergSparkSessionExtensions
    --conf spark.sql.catalog.spark_catalog=org.apache.iceberg.spark.SparkSessionCatalog
    --conf spark.sql.catalog.spark_catalog.type=hive
   ```

2. Create a `products` table in Hive Metastore. This is the source table, which already exists in a typical migration.

   a. Create the `products` external Hive table in Hive Metastore to point to the existing data in Amazon S3:

   ```
   spark.sql(f"""
   CREATE EXTERNAL TABLE products (
       product_id INT,
       product_name STRING
   )
   PARTITIONED BY (category STRING)
   STORED AS PARQUET
   LOCATION 's3://amzn-s3-demo-bucket/products/';
   """
   )
   ```

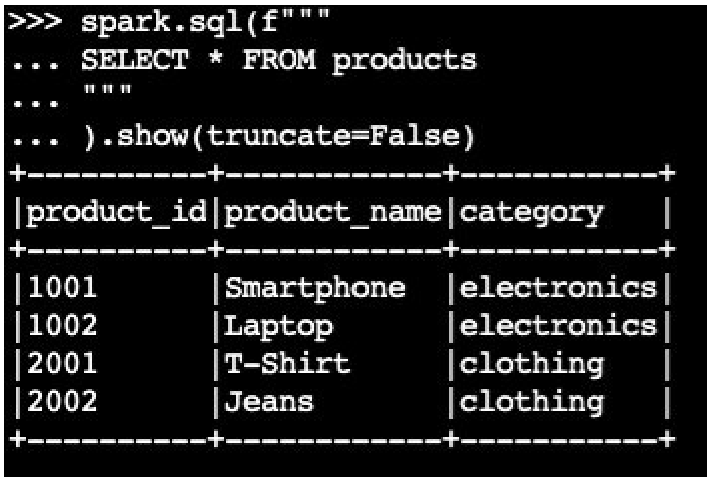
   b. Add the existing partitions by using the `MSCK REPAIR TABLE` command:

   ```
   spark.sql(f"""
   MSCK REPAIR TABLE products
   """
   )
   ```

c. Confirm that the table contains data by running a `SELECT` query:

```
spark.sql(f"""
SELECT * FROM products
"""
).show(truncate=False)
```

Sample output:



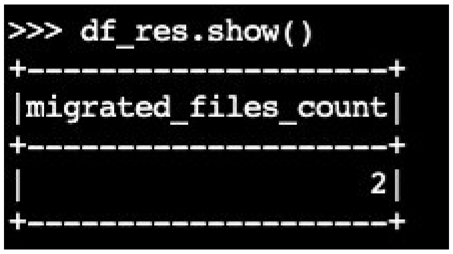
```
>>> spark.sql(f"""
... SELECT * FROM products
... """
... ).show(truncate=False)
+----------+------------+-----------+
|product_id|product_name|category   |
+----------+------------+-----------+
|1001      |Smartphone  |electronics|
|1002      |Laptop      |electronics|
|2001      |T-Shirt     |clothing   |
|2002      |Jeans       |clothing   |
+----------+------------+-----------+
```

3. Use the Iceberg `migrate` procedure:

```
df_res=spark.sql(f"""
CALL system.migrate(
table => 'default.products'
)
"""
)

df_res.show()
```

The output dataframe contains the `migrated_files_count` (the numbers of files that were added to the Iceberg table):

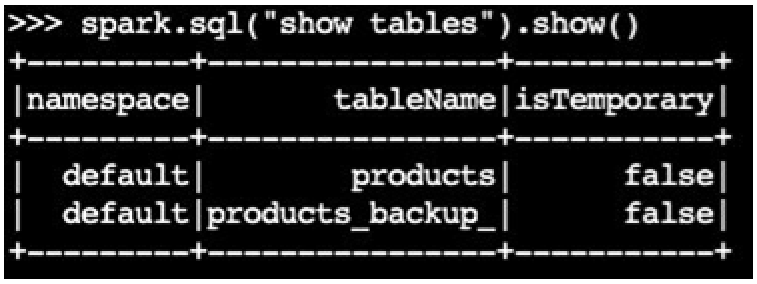


```
>>> df_res.show()
+--------------------+
|migrated_files_count|
+--------------------+
|                   2|
+--------------------+
```

4. Confirm that the backup table was created:

```
spark.sql("show tables").show()
```

Sample output:



```
>>> spark.sql("show tables").show()
+---------+----------------+-----------+
|namespace|       tableName|isTemporary|
+---------+----------------+-----------+
|  default|        products|      false|
|  default|products_backup_|      false|
+---------+----------------+-----------+
```

5. Validate the operation by querying the Iceberg table:

```
spark.sql(f"""
SELECT * FROM products
"""
).show(truncate=False)
```

Notes

- After you run the procedure, all current processes that query or write to the source table will be impacted if they aren't properly configured with Iceberg support. Therefore, we recommend that you follow these steps:
  1. Stop all processes by using the source table before migration.
  2. Perform the migration.
  3. Reactivate the processes by using the proper Iceberg settings.
- If data file modifications occur during the migration process (new files are added or files are removed), the generated table will get out of sync. For synchronization options, see Keeping Iceberg tables in sync after in-place migration later in this section.

Replicating the table migration procedure in AWS Glue Data Catalog

You can replicate the migrate procedure's outcome in AWS Glue Data Catalog (backing up the original table and replacing it with an Iceberg table) by following these steps:

1. Use the snapshot procedure to create a new Iceberg table that points to the original table's data files.
2. Back up the original table metadata in the Data Catalog:
   a. Use the GetTable API to retrieve the source table definition.
   b. Use the GetPartitions API to retrieve the source table partition definition.
   c. Use the CreateTable API to create a backup table in the Data Catalog.
   d. Use the CreatePartition or BatchCreatePartition API to register partitions to the backup table in the Data Catalog.
3. Change the `gc.enabled` Iceberg table property to `false` to enable full table operations.
4. Drop the original table.
5. Locate the Iceberg table metadata JSON file in the metadata folder of the table's root location.
6. Register the new table in the Data Catalog by using the register_table procedure with the original table name and the location of the `metadata.json` file that was created by the `snapshot` procedure:

```
spark.sql(f"""
CALL system.register_table(
    table => 'mydb.products',
    metadata_file => '{iceberg_metadata_file}'
)
"""
).show(truncate=False)
```

Keeping Iceberg tables in sync after in-place migration

The `add_files` procedure provides a flexible way to incorporate existing data into Iceberg tables. Specifically, it registers existing data files (such as Parquet files) by referencing their absolute paths in Iceberg's metadata layer. By default, the procedure adds files from all table partitions to an Iceberg table, but you can selectively add files from specific partitions. This selective approach is particularly useful in several scenarios:

- When new partitions are added to the source table after initial migration.
- When data files are added to or removed from existing partitions after initial migration. However, re-adding modified partitions requires partition deletion first. More information about this is provided later in this section.

Here are some considerations for using the `add_file` procedure after in-place migration (`snapshot` or `migrate`) has been performed, to keep the new Iceberg table in sync with the source data files:

- When new data is added to new partitions in the source table, use the `add_files` procedure with the `partition_filter` option to selectively incorporate these additions into the Iceberg table:

  ```
  spark.sql(f"""
  CALL system.add_files(
  source_table => 'mydb.products',
  table => 'mydb.products_iceberg',
  partition_filter => map('category', 'electronics')
  ).show(truncate=False)
  ```

  or:

  ```
  spark.sql(f"""
  CALL system.add_files(
  source_table => '`parquet`.`s3://amzn-s3-demo-bucket/products/`',
  table => 'mydb.products_iceberg',
  partition_filter => map('category', 'electronics')
  ).show(truncate=False)
  ```

- The `add_files` procedure scans for files either in the entire source table or in specific partitions when you specify the `partition_filter` option, and attempts to add all files it finds to the Iceberg table. By default, the `check_duplicate_files` procedure property is set to `true`, which prevents the procedure from running if files already exist in the Iceberg table. This is important because there is no built-in option to skip previously added files, and disabling `check_duplicate_files` will cause files to be added twice, creating duplicates. When new files are added to the source table, follow these steps:

  1. For new partitions, use `add_files` with a `partition_filter` to import only files from the new partition.
  2. For existing partitions, first delete the partition from the Iceberg table, and then re-run `add_files` for that partition, specifying the `partition_filter`. For example:

     ```
     # We initially perform in-place migration with snapshot
     spark.sql(f"""
     CALL system.snapshot(
     ```

```
source_table => 'mydb.products',
table => 'mydb.products_iceberg',
location => 's3://amzn-s3-demo-bucket/products_iceberg/'
)
"""
).show(truncate=False)

# Then on the source table, some new files were generated under the
 category='electronics' partition. Example:
spark.sql("""
INSERT INTO mydb.products
VALUES (1003, 'Tablet', 'electronics')
""")

# We delete the modified partition from the Iceberg table. Note this is a metadata
 operation only
spark.sql("""
DELETE FROM mydb.products_iceberg WHERE category = 'electronics'
""")

# We add_files from the modified partition
spark.sql("""
CALL system.add_files(
  source_table => 'mydb.products',
  table => 'mydb.products_iceberg',
  partition_filter => map('category', 'electronics')
)
""").show(truncate=False)
```

Note

Every `add_files` operation generates a new Iceberg table snapshot with appended data.

Choosing the right in-place migration strategy

To choose the best in-place migration strategy, consider the questions in the following table.

Question	Recommendation	Explanation
Do you want to quickly migrate without rewriting data while keeping both Hive and Iceberg tables accessibl e for testing or gradual transition?	`snapshot` procedure followed by `add_files` procedure	Use the `snapshot` procedure to create a new Iceberg table by cloning the schema and referencing data files, without modifying the source table. Use the `add_files` procedure to incorporate partitions that were added or modified after migration , noting that re-adding modified partitions requires partition deletion first.
Are you using Hive Metastore and do you want to replace your Hive table with an Iceberg table immediately, without rewriting the data?	`migrate` procedure followed by `add_files` procedure	Use the `migrate` procedure to create an Iceberg table, back up the source table, and replace the original table with the Iceberg version. **Note:** This option is compatibl e with Hive Metastore but not with AWS Glue Data Catalog. Use the `add_files` procedure to incorporate partitions that were added or modified after migration , noting that re-adding modified partitions requires partition deletion first.
Are you using AWS Glue Data Catalog and do you want to replace your Hive table with	Adaptation of the `migrate` procedure, followed by `add_files` procedure	Replicate `migrate` procedure behavior: 1. Use `snapshot` to create an Iceberg table.

Question	Recommendation	Explanation
an Iceberg table immediately, without rewriting the data?		2. Back up the original table metadata by using AWS Glue APIs. 3. Enable `gc.enabled` on Iceberg table properties. 4. Drop the original table. 5. Use `register_table` to create a new table entry with the original name. **Note:** This option requires manual handling of AWS Glue API calls for metadata backup. Use the `add_files` procedure to incorporate partitions that were added or modified after migration , noting that re-adding modified partitions requires partition deletion first.

Full data migration

Full data migration recreates the data files as well as the metadata. This approach takes longer and requires additional computing resources compared with in-place migration. However, full data migration offers significant opportunities to improve table quality and optimize data storage and access patterns.

During full data migration, you can perform several beneficial operations, such as data validation to ensure integrity and correctness, schema modifications to better meet current requirements, and partition strategy adjustments for improved query performance. You can also re-sort data to optimize common access patterns, implement Iceberg hidden partitioning for enhanced query efficiency, and perform file format conversion (for example, from CSV to Parquet) if desired.

These capabilities make full data migration ideal for transitioning to Iceberg format and for comprehensively refining and optimizing your data storage strategy. Although full data migration requires more time and resources up front, the resulting improvements in data quality, organization, and query performance can provide long-term benefits. To implement full data migration, use one of the following options:

- Use the `CREATE TABLE ... AS SELECT` (CTAS) statement in Spark (on Amazon EMR or AWS Glue) or in Athena. You can set the partition specification and table properties for the new Iceberg table by using the `PARTITIONED BY` and `TBLPROPERTIES` clauses. You can change the schema and partitioning for the new table according to your needs instead of inheriting them from the source table.
- Read from the source table and write the data as a new Iceberg table by using Spark on Amazon EMR or AWS Glue. For more information, see Creating a table in the Iceberg documentation.

Choosing a migration strategy

When transitioning to Iceberg format, the choice between in-place and full migration is crucial. To determine the most suitable approach for your specific needs, consider the following questions and recommendations:

Question	Recommendation
What is the data file format (for example, CSV or Apache Parquet)?	• Consider in-place migration if your table file format is Parquet, ORC, or Avro. • For other formats such as CSV, JSON, and so on, use full data migration.
Do you want to update or consolidate the table schema?	• If you want to evolve the table schema by using Iceberg native capabilities, consider in-place migration. For example, you can rename columns after the migration. (The schema can be changed in the Iceberg metadata layer.)

Question	Recommendation
	• If you want to remove entire columns because they are no longer needed, we recommend that you use full data migration.
Would the table benefit from changing the partition strategy?	• If Iceberg's partitioning approach meets your requirements (for example, new data is stored by using the new partition layout while existing partitions remain as is), consider in-place migration. • If you want to use hidden partitions in your table, consider full data migration. For more information about hidden partitions, see the Best practices section.
Would the table benefit from adding or changing the sort order strategy?	• Adding or changing the sort order of your data requires rewriting the dataset. In this case, consider using full data migration. • For large tables where it's prohibitively expensive to rewrite all the table partitions, consider using in-place migration and run compaction (with sorting enabled) for the most frequently accessed partitions.
Does the table have many small files?	• Merging small files into larger files requires rewriting the dataset. In this case, consider using full data migration. • For large tables where it's prohibitively expensive to rewrite all the table partitions, consider using in-place migration and run compaction (with sorting enabled) for the most frequently accessed partitions.

Migration options summary

This table summarizes the main characteristics and considerations for each migration option.

Feature	In-place migration snapshot	In-place migration migrate	Full data migration CTAS or (CREATE TABLE + INSERT)
Data layout improvements as part of the migratio process			
• Re-sort data	✗ N	✗ N	✓ Yes
• Chang partiti ing (for examp to use Iceber hidden partiti ing)	✗ N	✗ N	✓ Yes
• Chang table schem	✗ N	✗ N	✓ Yes
• Optim file size	✗ N	✗ N	✓ Yes

Feature	In-place migration snapshot	In-place migration migrate	Full data migration CTAS or (CREATE TABLE + INSERT)
• Valida the schem of existin data before adding the data	✗ N	✗ N	✓ Yes
Support file formats	Parquet, Avro, ORC	Parquet, Avro, ORC	Parquet, Avro, ORC, JSON, CSV
Source table replacen nt by an Iceberg table	✗ N (creates a new table, but with additional steps you can replace the source table)	✓ Y (creates a backup table and substitutes the source table with an Iceberg table)	✗ No (creates a new table)
Source table impact			

Feature	In-place migration snapshot	In-place migration migrate	Full data migration CTAS or (CREATE TABLE + INSERT)
• File deletic operat s on Iceberg table (`expi apsho` operat s, droppi a table with purge)	Corrupts source table	Corrupts backup table	Safe, source unaffected
Iceberg table impact			
• Impac if source table files are remov	Corrupts Iceberg table	Corrupts Iceberg table	No impact on Iceberg table

Feature	In-place migration snapshot	In-place migration migrate	Full data migration CTAS or (CREATE TABLE + INSERT)
• Impac if new files are added on source table locatic	Not visible on new table (need to incorporate partition with `add_files`)	Not visible on new table (need to incorporate partition with `add_files`)	Not visible on new table (need to `INSERT INTO` the new table)
Cost	Low	Low	Higher (full data rewrite)
Migratio speed	Fast	Fast	Slower
Can be used to migrate to Amazon S3 Tables	✗ N	✗ N	✓ Yes
Requires manual DDL	✗ N (schema and partitions are copied from source table)	✗ N (schema and partitions are copied from source table)	If using CTAS, requires only specifyin g the partitioning

Feature	In-place migration snapshot	In-place migration migrate	Full data migration CTAS or (CREATE TABLE + INSERT)
Best use	Quick migration without rewriting data, allowing side-by-side use of Hive and Iceberg for testing or gradual transitio n.	Replacing a Hive table in place without rewriting data, when an immediate switchover is acceptable.	Full Iceberg optimization with data rewrite. Ideal when redesigning partitions or schema, or improving layout and performance. Always recommended if possible.

Best practices for optimizing Apache Iceberg workloads

Iceberg is a table format that's designed to simplify data lake management and enhance workload performance. Different use cases might prioritize different aspects such as cost, read performance, write performance, or data retention, so Iceberg offers configuration options to manage these trade-offs. This section provides insights for optimizing and fine-tuning your Iceberg workloads to meet your requirements.

Topics

General best practices

Regardless of your use case, when you use Apache Iceberg on AWS, we recommend that you follow these general best practices.

- **Use Iceberg format version 2.**

  Athena uses Iceberg format version 2 by default.

  When you use Spark on Amazon EMR or AWS Glue to create Iceberg tables, specify the format version as described in the Iceberg documentation.
- **Use the AWS Glue Data Catalog as your data catalog.**

  Athena uses the AWS Glue Data Catalog by default.

  When you use Spark on Amazon EMR or AWS Glue to work with Iceberg, add the following configuration to your Spark session to use the AWS Glue Data Catalog. For more information, see the section Spark configurations for Iceberg in AWS Glue earlier in this guide.

  ```
  "spark.sql.catalog.<your_catalog_name>.type": "glue"
  ```

- **Use the AWS Glue Data Catalog as lock manager.**

  Athena uses the AWS Glue Data Catalog as lock manager by default for Iceberg tables.

  When you use Spark on Amazon EMR or AWS Glue to work with Iceberg, make sure to configure your Spark session configuration to use the AWS Glue Data Catalog as lock manager. For more information, see Optimistic Locking in the Iceberg documentation.
- **Use Zstandard (ZSTD) compression.**

  The default compression codec of Iceberg is gzip, which can be modified by using the table property `write.<file_type>.compression-codec`. Athena already uses ZSTD as the default compression codec for Iceberg tables.

  In general, we recommend using the ZSTD compression codec because it strikes a balance between GZIP and Snappy, and offers good read/write performance without compromising the compression ratio. Additionally, compression levels can be adjusted to suit your needs. For more information, see ZSTD compression levels in Athena in the Athena documentation.

  Snappy might provide the best overall read and write performance but has a lower compression ratio than GZIP and ZSTD. If you prioritize performance—even if it means storing larger data volumes in Amazon S3—Snappy might be the optimal choice.

Optimizing read performance

This section discusses table properties that you can tune to optimize read performance, independent of the engine.

Partitioning

As with Hive tables, Iceberg uses partitions as the primary layer of indexing to avoid reading unnecessary metadata files and data files. Column statistics are also taken into consideration as a secondary layer of indexing to further improve query planning, which leads to better overall execution time.

Partition your data

To reduce the amount of data that's scanned when querying Iceberg tables, choose a balanced partition strategy that aligns with your expected read patterns:

- Identify columns that are frequently used in queries. These are ideal partitioning candidates. For example, if you typically query data from a particular day, a natural example of a partition column would be a date column.
- Choose a low cardinality partition column to avoid creating an excessive number of partitions. Too many partitions can increase the number of files in the table, which can negatively impact query performance. As a rule of thumb, "too many partitions" can be defined as a scenario where the data size in the majority of partitions is less than 2-5 times the value set by `target-file-size-bytes`.

Note

If you typically query by using filters on a high cardinality column (for example, an `id` column that can have thousands of values), use Iceberg's hidden partitioning feature with bucket transforms, as explained in the next section.

Use hidden partitioning

If your queries commonly filter on a derivative of a table column, use hidden partitions instead of explicitly creating new columns to work as partitions. For more information about this feature, see the Iceberg documentation.

For example, in a dataset that has a timestamp column (for example, `2023-01-01 09:00:00`), instead of creating a new column with the parsed date (for example, `2023-01-01`), use partition transforms to extract the date part from the timestamp and create these partitions on the fly.

The most common use cases for hidden partitioning are:

- **Partitioning on date or time**, when the data has a timestamp column. Iceberg offers multiple transforms to extract the date or time parts of a timestamp.
- **Partitioning on a hash function of a column**, when the partitioning column has high cardinality and would result in too many partitions. Iceberg's bucket transform groups multiple partition values together into fewer, hidden (bucket) partitions by using hash functions on the partitioning column.

See partition transforms in the Iceberg documentation for an overview of all available partition transforms.

Columns that are used for hidden partitioning can become part of query predicates through the use of regular SQL functions such as `year()` and `month()`. Predicates can also be combined with operators such as `BETWEEN` and `AND`.

Note

Iceberg cannot perform partition pruning for functions that yield a different data type; for example, `substring(event_time, 1, 10) = '2022-01-01'`.

Use partition evolution

Use Iceberg's partition evolution when the existing partition strategy isn't optimal. For example, if you choose hourly partitions that turn out to be too small (just a few megabytes each), consider shifting to daily or monthly partitions.

You can use this approach when the best partition strategy for a table is initially unclear, and you want to refine your partitioning strategy as you gain more insights. Another effective use of partition evolution is when data volumes change and the current partitioning strategy becomes less effective over time.

For instructions on how to evolve partitions, see ALTER TABLE SQL extensions in the Iceberg documentation.

Tuning file sizes

Optimizing query performance involves minimizing the number of small files in your tables. For good query performance, we generally recommend keeping Parquet and ORC files larger than 100 MB.

File size also impacts query planning for Iceberg tables. As the number of files in a table increases, so does the size of the metadata files. Larger metadata files can result in slower query planning. Therefore, when the table size grows, increase the file size to alleviate the exponential expansion of metadata.

Use the following best practices to create properly sized files in Iceberg tables.

Set target file and row group size

Iceberg offers the following key configuration parameters for tuning the data file layout. We recommend that you use these parameters to set the target file size and row group or strike size.

Parameter	Default value	Comment
`write.target-file-size-bytes`	512 MB	This parameter specifies the maximum file size that Iceberg will create. However, certain files might be written with a smaller size than this limit.
`write.parquet.row-group-size-bytes`	128 MB	Both Parquet and ORC store data in chunks so that engines can avoid reading the entire file for some operation s.
`write.orc.stripe-size-bytes`	64 MB	
`write.distribution-mode`	None, for Iceberg version 1.1 and lower Hash, starting with Iceberg version 1.2	Iceberg requests Spark to sort data between its tasks before writing to storage.

- Based on your expected table size, follow these general guidelines:
  - **Small tables** (up to few gigabytes) – Reduce the target file size to 128 MB. Also reduce the row group or stripe size (for example, to 8 or 16 MB).
  - **Medium to large tables** (from a few gigabytes to hundreds of gigabytes) – The default values are a good starting point for these tables. If your queries are very selective, adjust the row group or stripe size (for example, to 16 MB).
  - **Very large tables** (hundreds of gigabytes or terabytes) – Increase the target file size to 1024 MB or more, and consider increasing the row group or stripe size if your queries usually pull large sets of data.

- To ensure that Spark applications that write to Iceberg tables create appropriately sized files, set the `write.distribution-mode` property to either `hash` or `range`. For a detailed explanation of the difference between these modes, see Writing Distribution Modes in the Iceberg documentation.

These are general guidelines. We recommend that you run tests to identify the most suitable values for your specific tables and workloads.

Run regular compaction

The configurations in the previous table set a maximum file size that write tasks can create, but do not guarantee that files will have that size. To ensure proper file sizes, run compaction regularly to combine small files into larger files. For detailed guidance on running compaction, see Iceberg compaction later in this guide.

Optimize column statistics

Iceberg uses column statistics to perform file pruning, which improves query performance by reducing the amount of data that's scanned by queries. To benefit from column statistics, make sure that Iceberg collects statistics for all columns that are frequently used in query filters.

By default, Iceberg collects statistics only for the first 100 columns in each table, as defined by the table property `write.metadata.metrics.max-inferred-column-defaults`. If your table has more than 100 columns and your queries frequently reference columns outside of the first 100 columns (for example, you might have queries that filter on column 132), make sure that Iceberg collects statistics on those columns. There are two options to achieve this:

- When you create the Iceberg table, reorder columns so that the columns you need for queries fall within the column range set by `write.metadata.metrics.max-inferred-column-defaults` (default is 100).

  Note: If you don't need statistics on 100 columns, you can adjust the `write.metadata.metrics.max-inferred-column-defaults` configuration to a desired value (for example, 20) and reorder the columns so that the columns you need to read and write queries fall within the first 20 columns on the left side of the dataset.
- If you use only a few columns in query filters, you can disable the overall property for metrics collection and selectively choose individual columns to collect statistics for, as shown in this example:

```
.tableProperty("write.metadata.metrics.default", "none")
```

```
.tableProperty("write.metadata.metrics.column.my_col_a", "full")
.tableProperty("write.metadata.metrics.column.my_col_b", "full")
```

Note: Column statistics are most effective when data is sorted on those columns. For more information, see the Set the sort order section later in this guide.

Choose the right update strategy

Use a copy-on-write strategy to optimize read performance, when slower write operations are acceptable for your use case. This is the default strategy used by Iceberg.

Copy-on-write results in better read performance, because files are directly written to storage in a read-optimized fashion. However, compared with merge-on-read, each write operation takes longer and consumes more compute resources. This presents a classic trade-off between read and write latency. Typically, copy-on-write is ideal for use cases where most updates are collocated in the same table partitions (for example, for daily batch loads).

Copy-on-write configurations (`write.update.mode`, `write.delete.mode`, and `write.merge.mode`) can be set at the table level or independently on the application side.

Use ZSTD compression

You can modify the compression codec used by Iceberg by using the table property `write.<file_type>.compression-codec`. We recommend that you use the ZSTD compression codec to improve overall performance on tables.

By default, Iceberg versions 1.3 and earlier use GZIP compression, which provides slower read/write performance compared with ZSTD.

Note: Some engines might use different default values. This is the case for Iceberg tables that are created with Athena or Amazon EMR version 7.x.

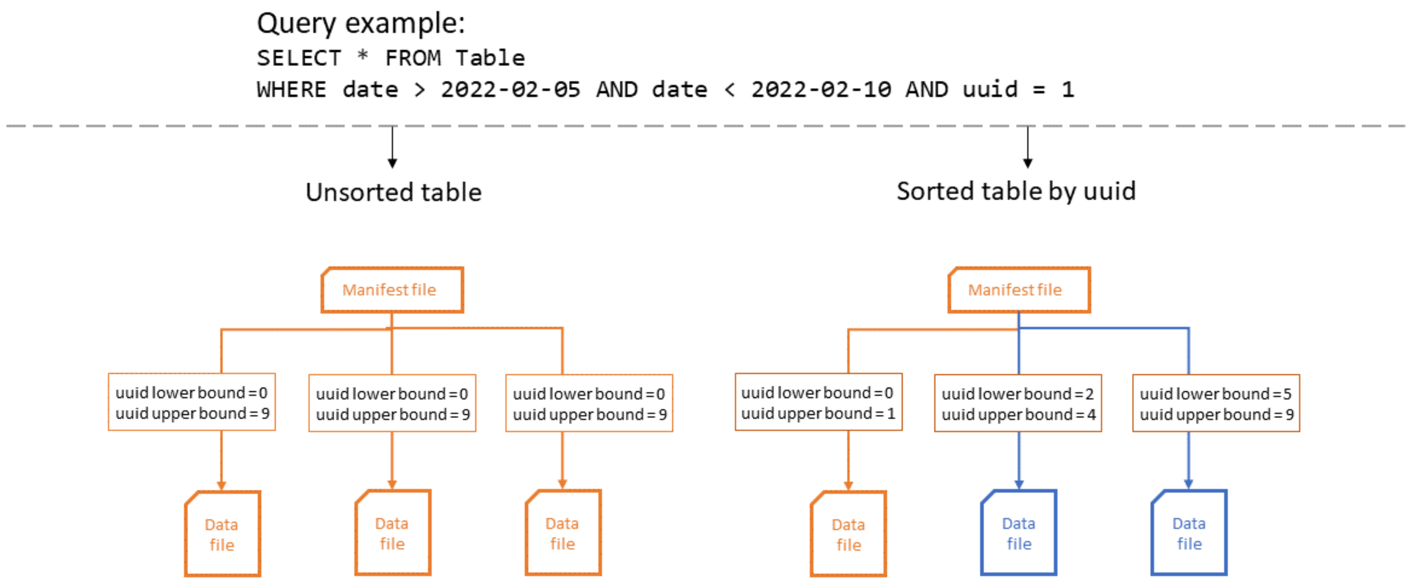
Set the sort order

To improve read performance on Iceberg tables, we recommend that you sort your table based on one or more columns that are frequently used in query filters. Sorting, combined with Iceberg's column statistics, can make file pruning significantly more efficient, which results in faster read operations. Sorting also reduces the number of Amazon S3 requests for queries that use the sort columns in query filters.

You can set a hierarchical sort order at the table level by running a data definition language (DDL) statement with Spark. For available options, see the Iceberg documentation. After you set the sort order, writers will apply this sorting to subsequent data write operations in the Iceberg table.

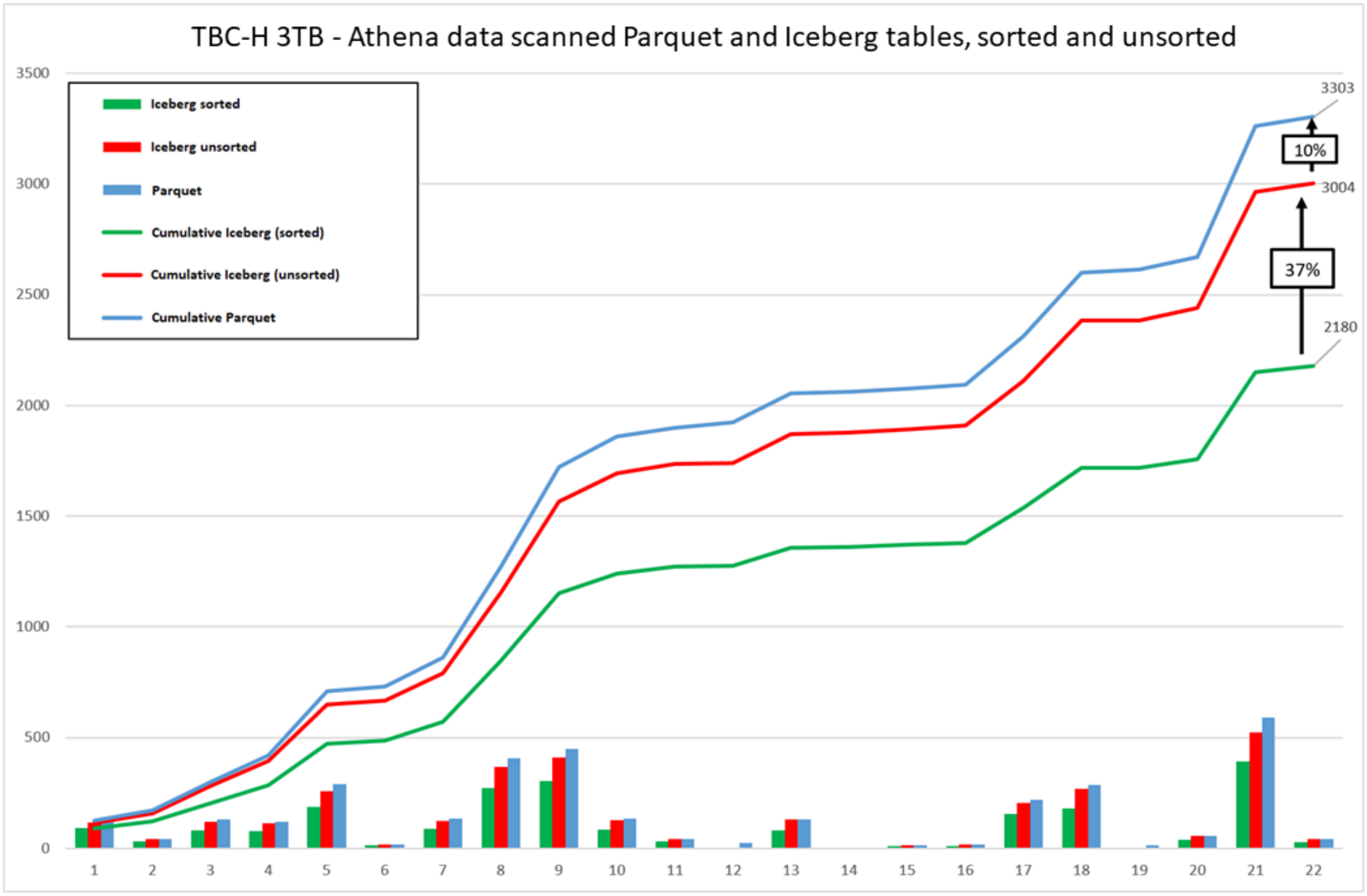
For example, in tables that are partitioned by date (`yyyy-mm-dd`) where most of the queries filter by `uuid`, you can use the DDL option `Write Distributed By Partition Locally Ordered` to make sure that Spark writes files with non-overlapping ranges.

The following diagram illustrates how the efficiency of column statistics improves when tables are sorted. In the example, the sorted table needs to open only a single file, and maximally benefits from Iceberg's partition and file. In the unsorted table, any `uuid` can potentially exist in any data file, so the query has to open all data files.

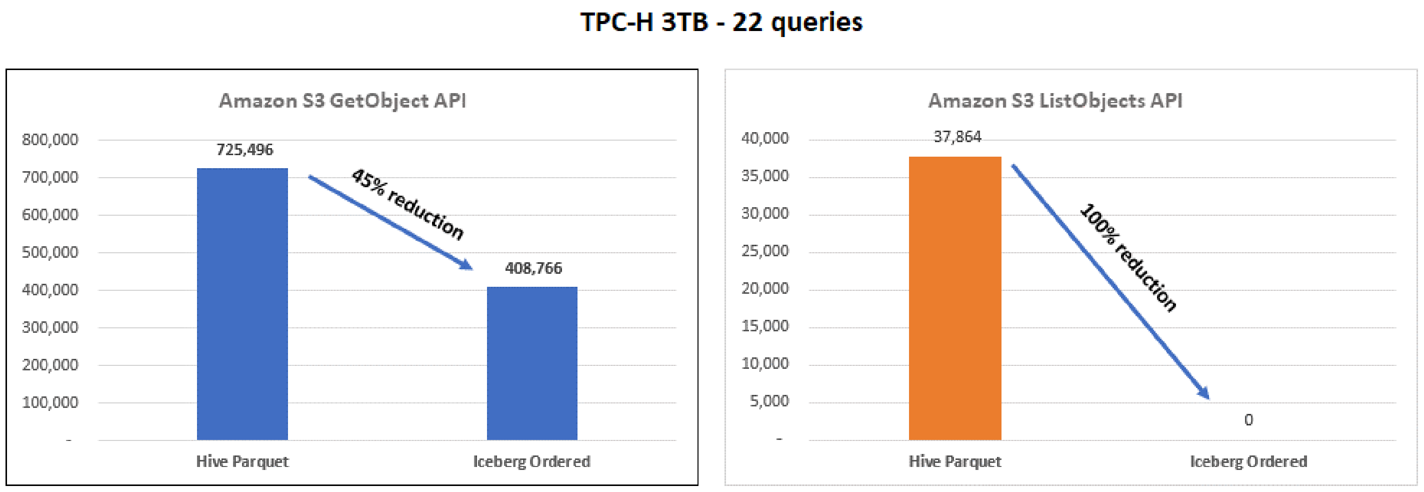


Changing the sort order doesn't affect existing data files. You can use Iceberg compaction to apply the sort order on those.

Using Iceberg sorted tables might decrease costs for your workload, as illustrated in the following graph.



These graphs summarize the results of running the TPC-H benchmark for Hive (Parquet) tables compared with Iceberg sorted tables. However, the results might be different for other datasets or workloads.



Optimizing write performance

This section discusses table properties that you can tune to optimize write performance on Iceberg tables, independent of the engine.

Set the table distribution mode

Iceberg offers multiple write distribution modes that define how write data is distributed across Spark tasks. For an overview of the available modes, see Writing Distribution Modes in the Iceberg documentation.

For use cases that prioritize write speed, especially in streaming workloads, set `write.distribution-mode` to `none`. This ensures that Iceberg doesn't request additional Spark shuffling and that data is written as it becomes available in Spark tasks. This mode is particularly suitable for Spark Structured Streaming applications.

Note

Setting the write distribution mode to `none` tends to produce numerous small files, which degrades read performance. We recommend regular compaction to consolidate these small files into properly sized files for query performance.

Choose the right update strategy

Use a merge-on-read strategy to optimize write performance, when slower read operations on the latest data are acceptable for your use case.

When you use merge-on-read, Iceberg writes updates and deletes to storage as separate small files. When the table is read, the reader has to merge these changes with the base files to return the latest view of the data. This results in a performance penalty for read operations, but speeds up the writing of updates and deletes. Typically, merge-on-read is ideal for streaming workloads with updates or jobs with few updates that are spread across many table partitions.

You can set merge-on-read configurations (`write.update.mode`, `write.delete.mode`, and `write.merge.mode`) at the table level or independently on the application side.

Using merge-on-read requires running regular compaction to prevent read performance from degrading over time. Compaction reconciles updates and deletes with existing data files to create a new set of data files, thereby eliminating the performance penalty incurred on the read side. By default, Iceberg's compaction doesn't merge delete files unless you change the default of the `delete-file-threshold` property to a smaller value (see the Iceberg documentation). To learn more about compaction, see the section Iceberg compaction later in this guide.

Choose the right file format

Iceberg supports writing data in Parquet, ORC, and Avro formats. Parquet is the default format. Parquet and ORC are columnar formats that offer superior read performance but are generally slower to write. This represents the typical trade-off between read and write performance.

If write speed is important for your use case, such as in streaming workloads, consider writing in Avro format by setting `write-format` to `Avro` in the writer's options. Because Avro is a row-based format, it provides faster write times at the cost of slower read performance.

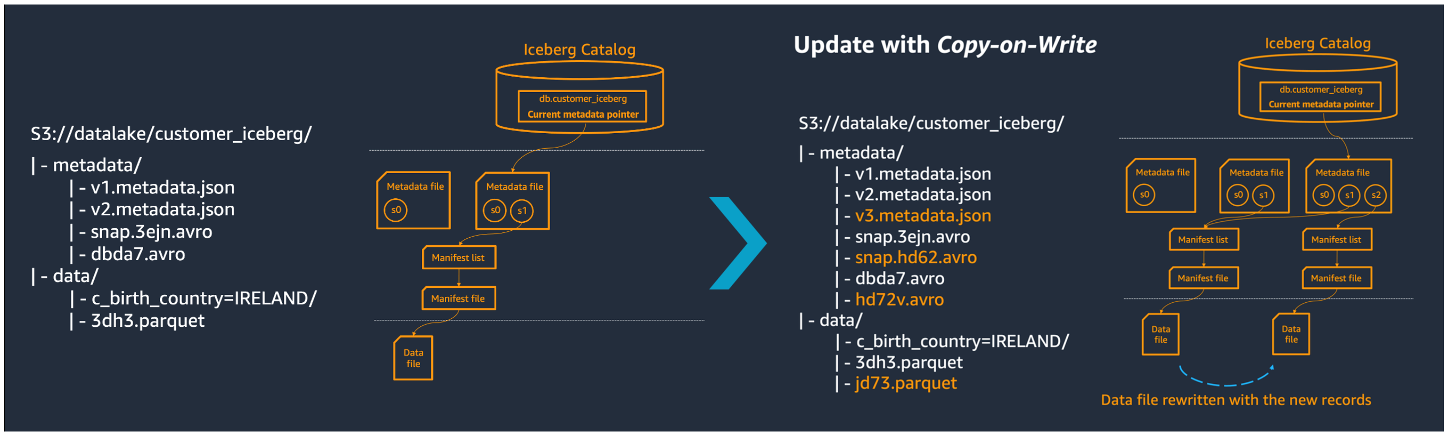
To improve read performance, run regular compaction to merge and transform small Avro files into larger Parquet files. The outcome of the compaction process is governed by the `write.format.default` table setting. The default format for Iceberg is Parquet, so if you write in Avro and then run compaction, Iceberg will transform the Avro files into Parquet files. Here's an example:

```
spark.sql(f"""
    CREATE TABLE IF NOT EXISTS glue_catalog.{DB_NAME}.{TABLE_NAME} (
        Col_1 float,
        <<<…other columns…>>
        ts timestamp)
    USING iceberg
    PARTITIONED BY (days(ts))
    OPTIONS (
      'format-version'='2',
      write.format.default'=parquet)
""")

query = df \
    .writeStream \
    .format("iceberg") \
    .option("write-format", "avro") \
    .outputMode("append") \
    .trigger(processingTime='60 seconds') \
    .option("path", f"glue_catalog.{DB_NAME}.{TABLE_NAME}") \
    .option("checkpointLocation", f"s3://{BUCKET_NAME}/checkpoints/iceberg/")
    .start()
```

Optimizing storage

Updating or deleting data in an Iceberg table increases the number of copies of your data, as illustrated in the following diagram. The same is true for running compaction: It increases the number of data copies in Amazon S3. That's because Iceberg treats the files underlying all tables as immutable.



```
S3://datalake/customer_iceberg/
| - metadata/
        | - v1.metadata.json
        | - v2.metadata.json
        | - snap.3ejn.avro
        | - dbda7.avro
| - data/
        | - c_birth_country=IRELAND/
        | - 3dh3.parquet
```

```
S3://datalake/customer_iceberg/
| - metadata/
        | - v1.metadata.json
        | - v2.metadata.json
        | - v3.metadata.json
        | - snap.3ejn.avro
        | - snap.hd62.avro
        | - dbda7.avro
        | - hd72v.avro
| - data/
        | - c_birth_country=IRELAND/
        | - 3dh3.parquet
        | - jd73.parquet
```

Follow the best practices in this section to manage storage costs.

Enable S3 Intelligent-Tiering

Use the Amazon S3 Intelligent-Tiering storage class to automatically move data to the most cost-effective access tier when access patterns change. This option has no operational overhead or impact on performance.

Note: Don't use the optional tiers (such as Archive Access and Deep Archive Access) in S3 Intelligent-Tiering with Iceberg tables. To archive data, see the guidelines in the next section.

You can also use Amazon S3 Lifecycle rules to set your own rules for moving objects to another Amazon S3 storage class, such as S3 Standard-IA or S3 One Zone-IA (see Supported transitions and related constraints in the Amazon S3 documentation).

Archive or delete historic snapshots

For every committed transaction (insert, update, merge into, compaction) to an Iceberg table, a new version or snapshot of the table is created. Over time, the number of versions and the number of metadata files in Amazon S3 accumulate.

Keeping snapshots of a table is required for features such as snapshot isolation, table rollback, and time travel queries. However, storage costs grow with the number of versions that you retain.

The following table describes the design patterns you can implement to manage costs based on your data retention requirements.

Design pattern	Solution	Use cases
Delete old snapshots	• Use the VACUUM statement in Athena to remove old snapshots. This operation doesn't incur any compute cost. • Alternatively, you can use Spark on Amazon EMR or AWS Glue to remove snapshots.For more information, see expire_snapshots in the Iceberg documentation.	This approach deletes snapshots that are no longer needed to reduce storage costs. You can configure how many snapshots should be retained or for how long, based on your data retention requirements. This option performs a hard delete of the snapshots. You can't roll back or time travel to expired snapshots.
Set retention policies for specific snapshots	1. Use tags to mark specific snapshots and define a retention policy in Iceberg. For more information, see Historical Tags in the Iceberg documentation. For example, you can retain one snapshot per month for one year by using the following SQL statement in Spark on Amazon EMR: `ALTER TABLE glue_catalog.db.table`	This pattern is helpful for compliance with business or legal requirements that require you to show the state of a table at a given point in the past. By placing retention policies on specific tagged snapshots, you can remove other (untagged) snapshots that were created. This way, you can meet data retention requirements without retaining every single snapshot created.

Design pattern	Solution	Use cases
	`CREATE TAG 'EOM-01' AS OF VERSION 30 RETAIN 365 DAYS` 2. Use Spark on Amazon EMR or AWS Glue to remove the remaining untagged, intermediate snapshots.	

Design pattern	Solution	Use cases
Archive old snapshots	1. Use Amazon S3 tags to mark objects with Spark. (Amazon S3 tags are different from Iceberg tags; for more information, see the Iceberg documentation.) For example: `spark.sql.catalog.my_catalog.s3.delete-enabled=false and \ spark.sql.catalog.my_catalog.s3.delete.tags.my_key=to_archive` 2. Use Spark on Amazon EMR or AWS Glue to remove snapshots. When you use the settings in the example, this procedure tags objects and detaches them from the Iceberg table metadata instead of deleting them from Amazon S3. 3. Use S3 Life cycle rules to transition objects tagged as `to_archive` to one of the S3 Glacier storage classes. 4. To query archived data: • Restore the archived objects (this step isn't required if objects were	This pattern allows you to keep all table versions and snapshots at a lower cost. You cannot time travel or roll back to archived snapshots without first restoring those versions as new tables. This is typically acceptable for audit purposes. You can combine this approach with the previous design pattern, setting retention policies for specific snapshots.

Design pattern	Solution	Use cases
	transitioned to the Amazon Glacier Instant Retrieval storage class). • Use the register_table procedure in Iceberg to register the snapshot as a table in the catalog. For detailed instructions, see the AWS blog post Improve operational efficiencies of Apache Iceberg tables build on Amazon S3 data lakes.	

Delete orphan files

In certain situations, Iceberg applications can fail before you commit your transactions. This leaves data files in Amazon S3. Because there was no commit, these files won't be associated with any table, so you might have to clean them up asynchronously.

To handle these deletions, you can use the VACUUM statement in Amazon Athena. This statement removes snapshots and also deletes orphaned files. This is very cost-efficient, because Athena doesn't charge for the compute cost of this operation. Also, you don't have to schedule any additional operations when you use the `VACUUM` statement.

Alternatively, you can use Spark on Amazon EMR or AWS Glue to run the `remove_orphan_files` procedure. This operation has a compute cost and has to be scheduled independently. For more information, see the Iceberg documentation.

Maintaining tables by using compaction

Iceberg includes features that enable you to carry out table maintenance operations after writing data to the table. Some maintenance operations focus on streamlining metadata files, while others enhance how the data is clustered in the files so that query engines can efficiently locate the necessary information to respond to user requests. This section focuses on compaction-related optimizations.

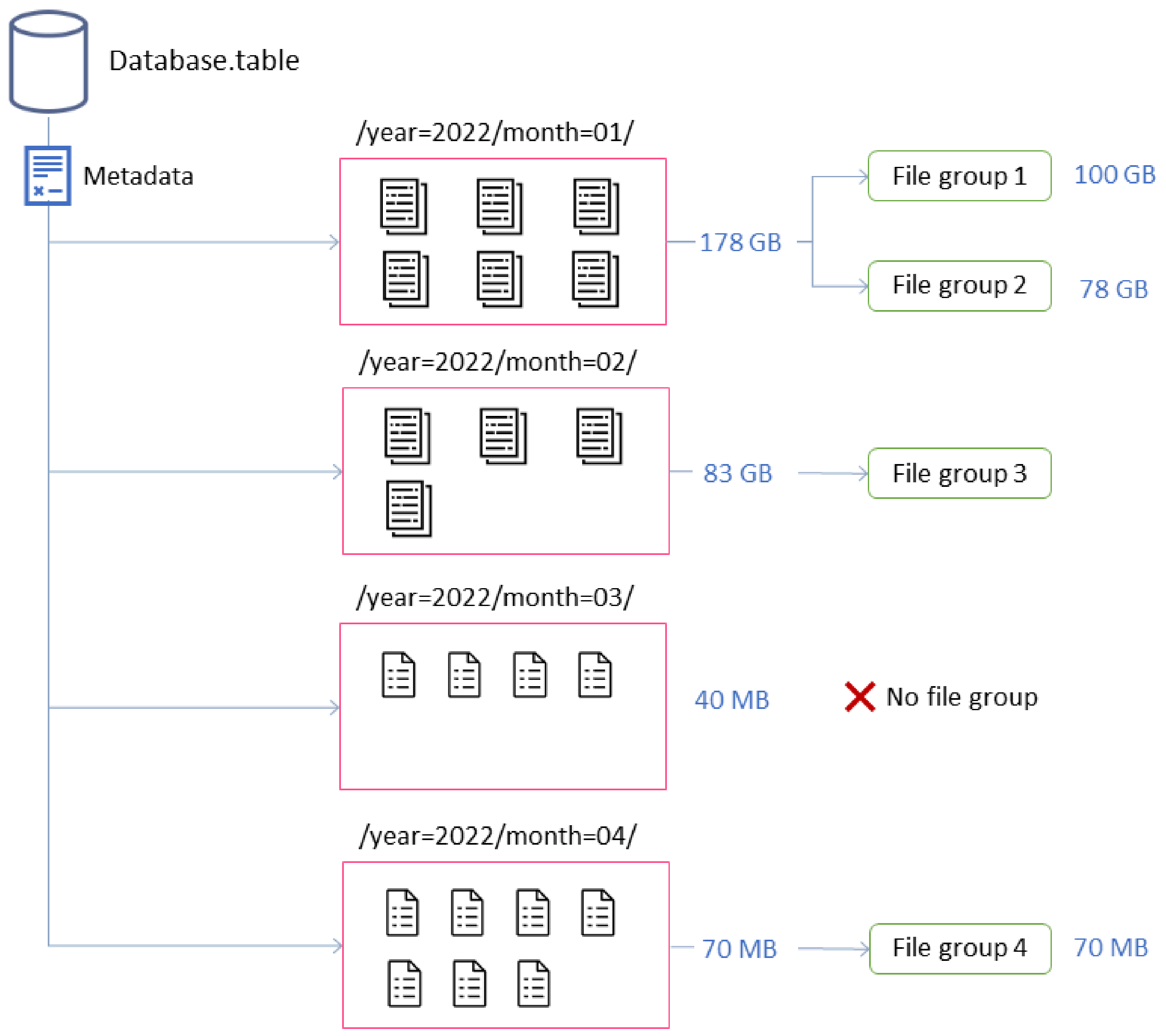
Iceberg compaction

In Iceberg, you can use compaction to perform four tasks:

- Combining small files into larger files that are generally over 100 MB in size. This technique is known as *bin packing*.
- Merging delete files with data files. Delete files are generated by updates or deletes that use the merge-on-read approach.
- (Re)sorting the data in accordance with query patterns. Data can be written without any sort order or with a sort order that is suitable for writes and updates.
- Clustering the data by using space filling curves to optimize for distinct query patterns, particularly z-order sorting.

On AWS, you can run table compaction and maintenance operations for Iceberg through Amazon Athena or by using Spark in Amazon EMR or AWS Glue.

When you run compaction by using the rewrite_data_files procedure, you can adjust several knobs to control the compaction behavior. The following diagram shows the default behavior of bin packing. Understanding bin packing compaction is key to understanding hierarchical sorting and Z-order sorting implementations, because they are extensions of the bin packing interface and operate in a similar manner. The main distinction is the additional step required for sorting or clustering the data.



In this example, the Iceberg table consists of four partitions. Each partition has a different size and different number of files. If you start a Spark application to run compaction, the application creates a total of four file groups to process. A file group is an Iceberg abstraction that represents a collection of files that will be processed by a single Spark job. That is, the Spark application that runs compaction will create four Spark jobs to process the data.

Tuning compaction behavior

The following key properties control how data files are selected for compaction:

- MAX_FILE_GROUP_SIZE_BYTES sets the data limit for a single file group (Spark job) at 100 GB by default. This property is especially important for tables without partitions or tables with partitions that span hundreds of gigabytes. By setting this limit, you can break down operations to plan work and make progress while preventing resource exhaustion on the cluster.

  Note: Each file group is sorted separately. Therefore, if you want to perform a partition-level sort, you must adjust this limit to match the partition size.
- MIN_FILE_SIZE_BYTES or MIN_FILE_SIZE_DEFAULT_RATIO defaults to 75 percent of the target file size set at the table level. For example, if a table has a target size of 512 MB, any file that is smaller than 384 MB is included in the set of files that will be compacted.
- MAX_FILE_SIZE_BYTES or MAX_FILE_SIZE_DEFAULT_RATIO defaults to 180 percent of the target file size. As with the two properties that set minimum file sizes, these properties are used to identify candidate files for the compaction job.
- MIN_INPUT_FILES specifies the minimum number of files to be compacted if a table partition size is smaller than the target file size. The value of this property is used to determine whether it is worthwhile to compact the files based on the number of files (defaults to 5).
- DELETE_FILE_THRESHOLD specifies the minimum number of delete operations for a file before it's included in compaction. Unless you specify otherwise, compaction doesn't combine delete files with data files. To enable this functionality, you must set a threshold value by using this property. This threshold is specific to individual data files, so if you set it to 3, a data file will be rewritten only if there are three or more delete files that reference it.

These properties provide insight into the formation of the file groups in the previous diagram.

For example, the partition labeled `month=01` includes two file groups because it exceeds the maximum size constraint of 100 GB. In contrast, the `month=02` partition contains a single file group because it's under 100 GB. The `month=03` partition doesn't satisfy the default minimum input file requirement of five files. As a result, it won't be compacted. Lastly, although the `month=04` partition doesn't contain enough data to form a single file of the desired size, the files will be compacted because the partition includes more than five small files.

You can set these parameters for Spark running on Amazon EMR or AWS Glue. For Amazon Athena, you can manage similar properties by using the table properties that start with the prefix `optimize_`).

Running compaction with Spark on Amazon EMR or AWS Glue

This section describes how to properly size a Spark cluster to run Iceberg's compaction utility. The following example uses Amazon EMR Serverless, but you can use the same methodology in Amazon EMR on EC2 or EKS, or in AWS Glue.

You can take advantage of the correlation between file groups and Spark jobs to plan the cluster resources. To process the file groups sequentially, considering the maximum size of 100 GB per file group, you can set the following Spark properties:

- `spark.dynamicAllocation.enabled` = `FALSE`
- `spark.executor.memory` = `20 GB`
- `spark.executor.instances` = `5`

If you want to speed up compaction, you can scale horizontally by increasing the number of file groups that are compacted in parallel. You can also scale Amazon EMR by using manual or dynamic scaling.

- **Manually scaling** (for example, by a factor of 4)
  - `MAX_CONCURRENT_FILE_GROUP_REWRITES` = `4` (our factor)
  - `spark.executor.instances` = `5` (value used in the example) x `4` (our factor) = `20`
  - `spark.dynamicAllocation.enabled` = `FALSE`
- **Dynamic scaling**
  - `spark.dynamicAllocation.enabled` = `TRUE` (default, no action required)
  - MAX_CONCURRENT_FILE_GROUP_REWRITES = `N` (align this value with `spark.dynamicAllocation.maxExecutors`, which is 100 by default; based on the executor configurations in the example, you can set `N` to 20)

  These are guidelines to help size the cluster. However, you should also monitor the performance of your Spark jobs to find the best settings for your workloads.

Running compaction with Amazon Athena

Athena offers an implementation of Iceberg's compaction utility as a managed feature through the OPTIMIZE statement. You can use this statement to run compaction without having to evaluate the infrastructure.

This statement groups small files into larger files by using the bin packing algorithm and merges delete files with existing data files. To cluster the data by using hierarchical sorting or z-order sorting, use Spark on Amazon EMR or AWS Glue.

You can change the default behavior of the `OPTIMIZE` statement at table creation by passing table properties in the `CREATE TABLE` statement, or after table creation by using the `ALTER TABLE` statement. For default values, see the Athena documentation.

Recommendations for running compaction

Use case	Recommendation
Running bin packing compaction based on a schedule	• Use the `OPTIMIZE` statement in Athena if you don't know how many small files your table contains. The Athena pricing model is based on the data scanned, so if there are no files to be compacted, there is no cost associated with these operations. To avoid encountering timeouts on Athena tables, run `OPTIMIZE` on a per-table-partition basis. • Use Amazon EMR or AWS Glue with dynamic scaling when you expect large volumes of small files to be compacted.
Running bin packing compaction based on events	• Use Amazon EMR or AWS Glue with dynamic scaling when you expect large volumes of small files to be compacted.
Running compaction to sort data	• Use Amazon EMR or AWS Glue, because sorting is an expensive operation and might need to spill data to disk.
Running compaction to cluster the data using z-order sorting	• Use Amazon EMR or AWS Glue, because z-order sorting is a very expensive operation and might need to spill data to disk.

Use case	Recommendation
Running compaction on partitions that might be updated by other applications because of late-arriving data	• Use Amazon EMR or AWS Glue. Enable the Iceberg PARTIAL_PROGRESS_ENABLED property. When you use this option, Iceberg splits the compaction output into multiple commits. If there is a collision (that is, if the data file is updated while compactio n is running), this setting reduces the cost of retry by limiting it to the commit that includes the affected file. Otherwise, you might have to recompact all files.
Running compaction on cold partitions (data partitions that no longer receive active writes)	• Use Amazon EMR or AWS Glue. In the `rewrite_data_files` procedure, specify a `where` predicate that excludes actively written partitions. This strategy prevents data conflicts between writers and compaction jobs, and leaves only metadata conflicts that Iceberg can automatically resolve.

Using Iceberg workloads in Amazon S3

This section discusses Iceberg properties that you can use to optimize Iceberg's interaction with Amazon S3.

Prevent hot partitioning (HTTP 503 errors)

Some data lake applications that run on Amazon S3 handle millions or billions of objects and process petabytes of data. This can lead to prefixes that receive a high volume of traffic, which are typically detected through HTTP 503 (service unavailable) errors. To prevent this issue, use the following Iceberg properties:

- Set `write.distribution-mode` to `hash` or `range` so that Iceberg writes large files, which results in fewer Amazon S3 requests. This is the preferred configuration and should address the majority of cases.

- If you continue to experience 503 errors due to an immense volume of data in your workloads, you can set `write.object-storage.enabled` to `true` in Iceberg. This instructs Iceberg to hash object names and distribute the load across multiple, randomized Amazon S3 prefixes.

For more information about these properties, see Write properties in the Iceberg documentation.

Use Iceberg maintenance operations to release unused data

To manage Iceberg tables, you can use the Iceberg core API, Iceberg clients (such as Spark), or managed services such as Amazon Athena. To delete old or unused files from Amazon S3, we recommend that you only use Iceberg native APIs to remove snapshots, remove old metadata files, and delete orphan files.

Using Amazon S3 APIs through Boto3, the Amazon S3 SDK, or the AWS Command Line Interface (AWS CLI), or using any other, non-Iceberg methods to overwrite or remove Amazon S3 files for an Iceberg table leads to table corruption and query failures.

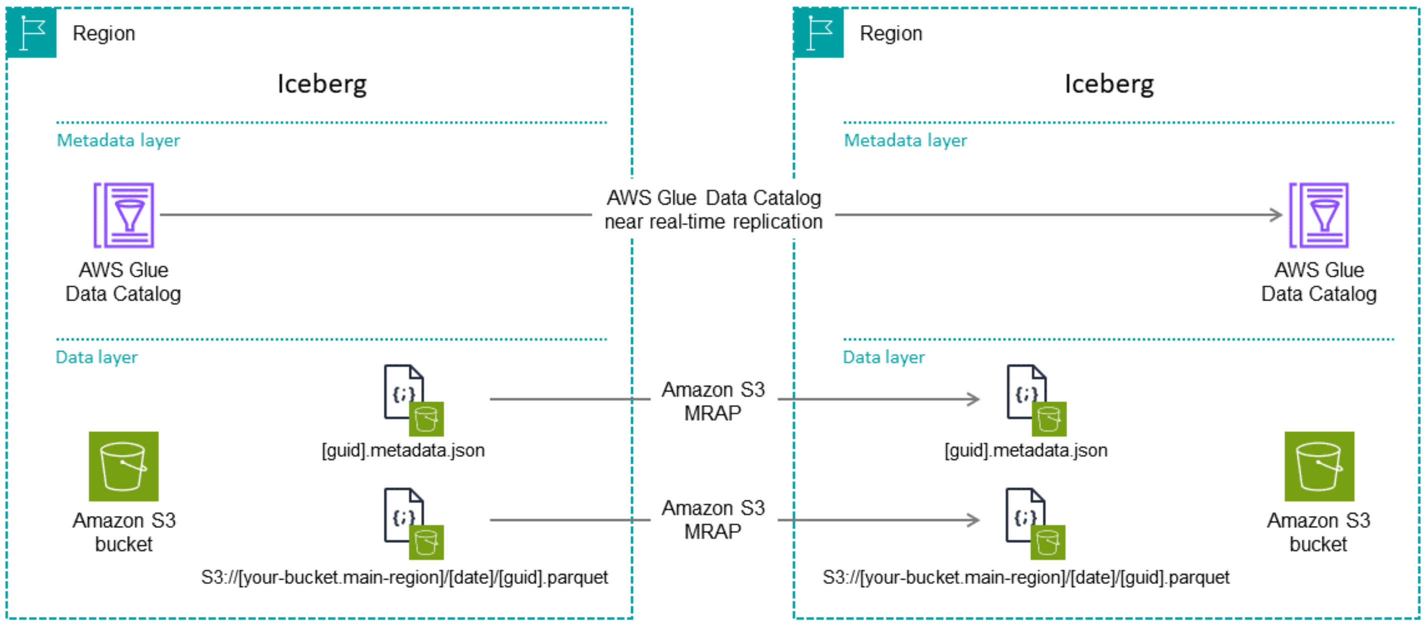
Replicate data across AWS Regions

When you store Iceberg tables in Amazon S3, you can use the built-in features in Amazon S3, such as Cross-Region Replication (CRR) and Multi-Region Access Points (MRAP), to replicate data across multiple AWS Regions. MRAP provides a global endpoint for applications to access S3 buckets that are located in multiple AWS Regions. Iceberg doesn't support relative paths, but you can use MRAP to perform Amazon S3 operations by mapping buckets to access points. MRAP also integrates seamlessly with the Amazon S3 Cross-Region Replication process, which introduces a lag of up to 15 minutes. You have to replicate both data and metadata files.

Important

Currently, Iceberg integration with MRAP works only with Apache Spark. If you need to fail over to the secondary AWS Region, you have to plan to redirect user queries to a Spark SQL environment (such as Amazon EMR) in the failover Region.

The CRR and MRAP features help you build a cross-Region replication solution for Iceberg tables, as illustrated in the following diagram.



To set up this cross-Region replication architecture:

1. Create tables by using the MRAP location. This ensures that Iceberg metadata files point to the MRAP location instead of the physical bucket location.
2. Replicate Iceberg files by using Amazon S3 MRAP. MRAP supports data replication with a service-level agreement (SLA) of 15 minutes. Iceberg prevents read operations from introducing inconsistencies during replication.
3. Make the tables available in the AWS Glue Data Catalog in the secondary Region. You can choose from two options:
   - Set up a pipeline for replicating Iceberg table metadata by using AWS Glue Data Catalog replication. This utility is available in the GitHub Glue Catalog and Lake Formation Permissions replication repository. This event-driven mechanism replicates tables in the target Region based on event logs.
   - Register the tables in the secondary Region when you need to fail over. For this option, you can use the previous utility or the Iceberg register_table procedure and point it to the latest `metadata.json` file.

Monitoring Apache Iceberg workloads

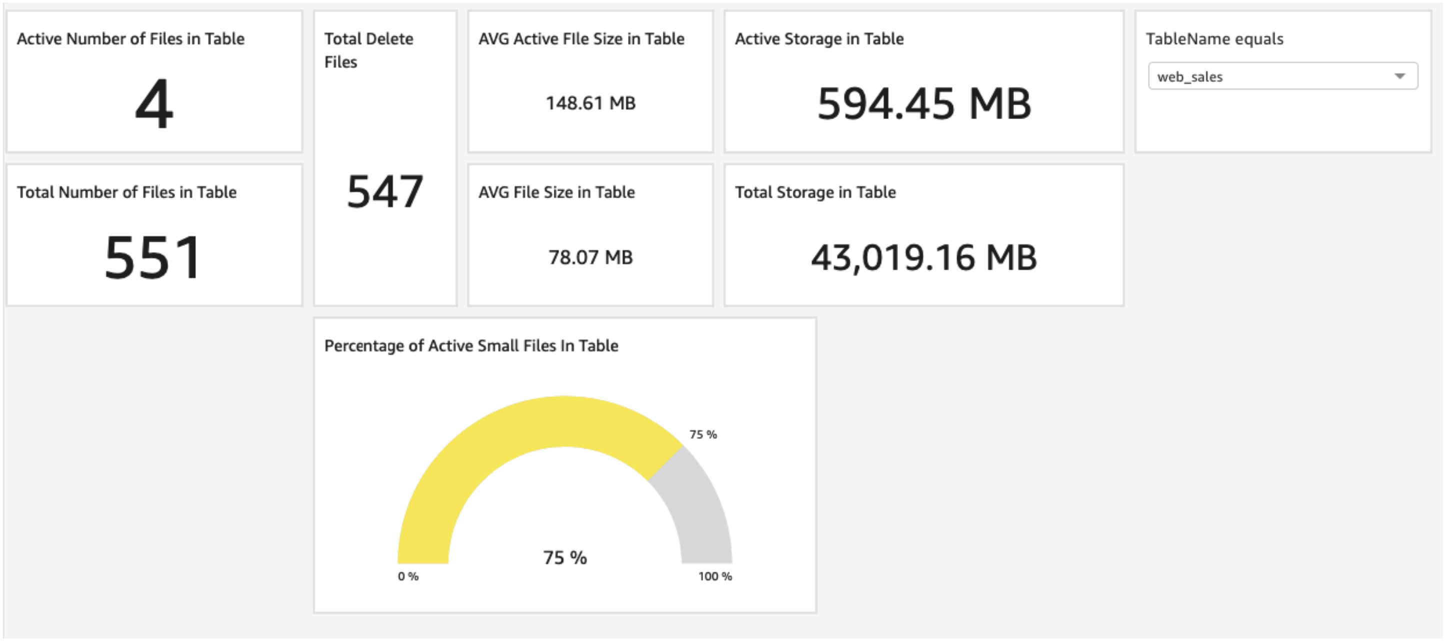
To monitor Iceberg workloads, you have two options: analyzing metadata tables or using metrics reporters. Metrics reporters were introduced in Iceberg version 1.2 and are available only for REST and JDBC catalogs.

If you're using AWS Glue Data Catalog, you can gain insights into the health of your Iceberg tables by setting up monitoring on top of the metadata tables that Iceberg exposes.

Monitoring is crucial for performance management and troubleshooting. For example, when a partition in an Iceberg table reaches a certain percentage of small files, your workload can start a compaction job to consolidate the files into larger ones. This prevents queries from slowing down beyond an acceptable level.

Table-level monitoring

The following screen shows a table monitoring dashboard that was created in Amazon Quick Sight. This dashboard queries Iceberg metadata tables by using Spark SQL, and captures detailed metrics such as the number of active files and total storage. This information is then stored in AWS Glue tables for operational purposes. Finally, a Quick Sight dashboard, as shown in the following illustration, is created by using Amazon Athena. This information helps you identify and address specific problems in your systems.



The example Quick Sight dashboard collects the following key performance indicators (KPIs) for an Iceberg table:

KPI	Description	Query

Number of files	The number of files in the Iceberg table (for all snapshots)	`select count(*)`
		`from <catalog.database.`
		`table_name>.all_files`

Number of active files	The number of active files in the last snapshot of the Iceberg table	`select count(*)`
		`from <catalog.database.`
		`table_name>.files`

Average file size	The average file size, in megabytes, for all files in the Iceberg table	`select avg(file_`
		`size_in_bytes)/100`
		`0000`
		`from <catalog.database.`
		`table_name>.all_files`

Average active file size	The average file size, in megabytes, for the active files in the Iceberg table	`select avg(file_`
		`size_in_bytes)/100`
		`0000`
		`from <catalog.database.`
		`table_name>.files`

Percentage of small files	The percentage of active files that are smaller than 100 MB	`select cast(sum(`
		`case when file_size`
		`_in_bytes < 100000000`
		` then 1 else 0 end)*100/`
		`count(*) as decimal(1`
		`0,2))`
		`from <catalog.database.`
		`table_name>.files`

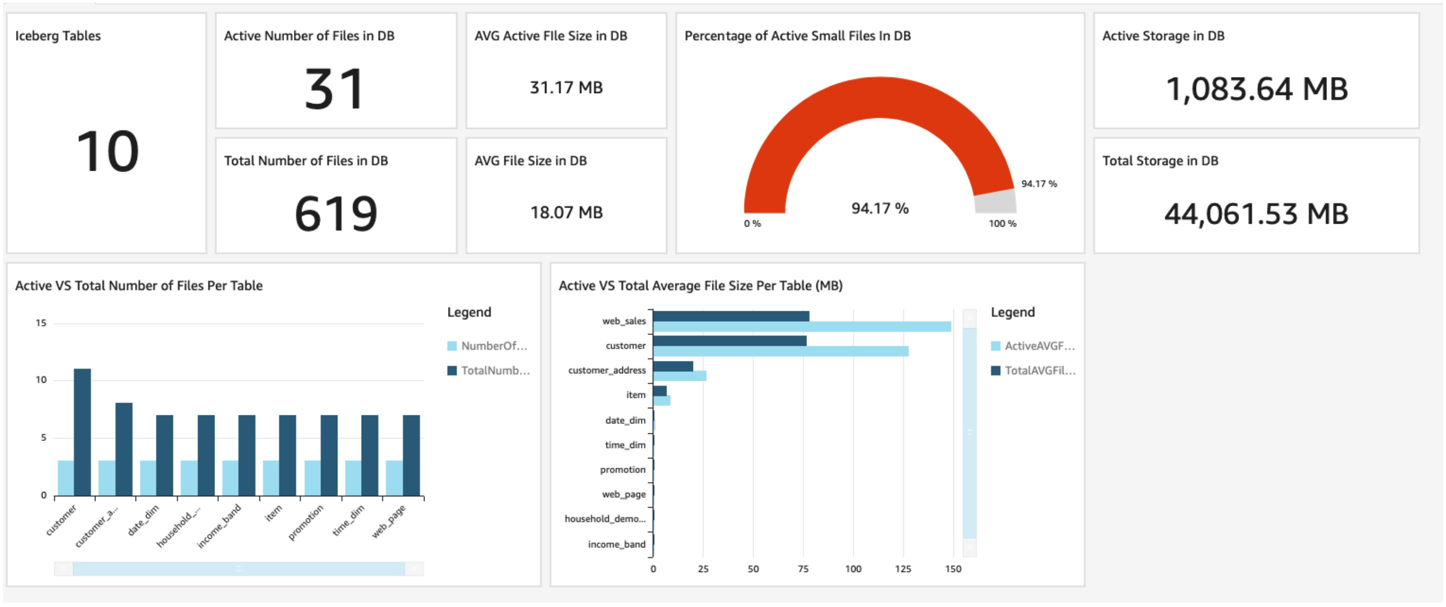
Total storage size	The total size of all the files in the table, excluding orphaned files and Amazon S3 object versions (if enabled)	`select sum(file_`
		`size_in_bytes)/100`
		`0000`

KPI	Description	Query
		`from <catalog.database.table_name>.all_files`
Total active storage size	The total size of all files in the current snapshots of a given table	`select sum(file_size_in_bytes)/1000000 from <catalog.database.table_name>.files`

For more information about creating dashboards, see the [Quick Sight documentation](#).

Database-level monitoring

The following example shows a monitoring dashboard that was created in Quick Sight to provide an overview of database-level KPIs for a collection of Iceberg tables.



This dashboard collects the following KPIs:

KPI	Description	Query
Number of files	The number of files in the Iceberg database (for all snapshots)	This dashboard uses the table-level queries provided in the previous section and consolidates the outcomes.
Number of active files	The number of active files in the Iceberg database (based on the last snapshots of Iceberg tables)	
Average file size	The average file size, in megabytes, for all files in the Iceberg database	
Average active file size	The average file size, in megabytes, for all active files in the Iceberg database	
Percentage of small files	The percentage of active files that are smaller than 100 MB in the Iceberg database	
Total Storage size	The total size of all files in the database, excluding orphaned files and Amazon S3 object versions (if enabled)	
Total active storage size	The total size of all files in the current snapshots of all tables in the database	

Preventive maintenance

By setting up the monitoring capabilities discussed in the previous sections, you can approach table maintenance from a preventive instead of reactive angle. For example, you can use the table-level and database-level metrics to schedule actions such as the following:

- Use bin packing compaction to group small files when a table reaches N small files.
- Use bin packing compaction to merge delete files when a table reaches N delete files in a given partition.
- Remove small files that were already compacted by removing snapshots when the total storage is X times higher than active storage.

Governance and access control for Apache Iceberg on AWS

Apache Iceberg integrates with AWS Lake Formation to simplify data governance. This integration allows data lake administrators to assign cell-level access permissions to Iceberg tables. For an example of querying Iceberg tables by using Amazon Athena and AWS Lake Formation, see the AWS blog post Interact with Apache Iceberg tables using Amazon Athena and cross account fine-grained permissions using AWS Lake Formation.

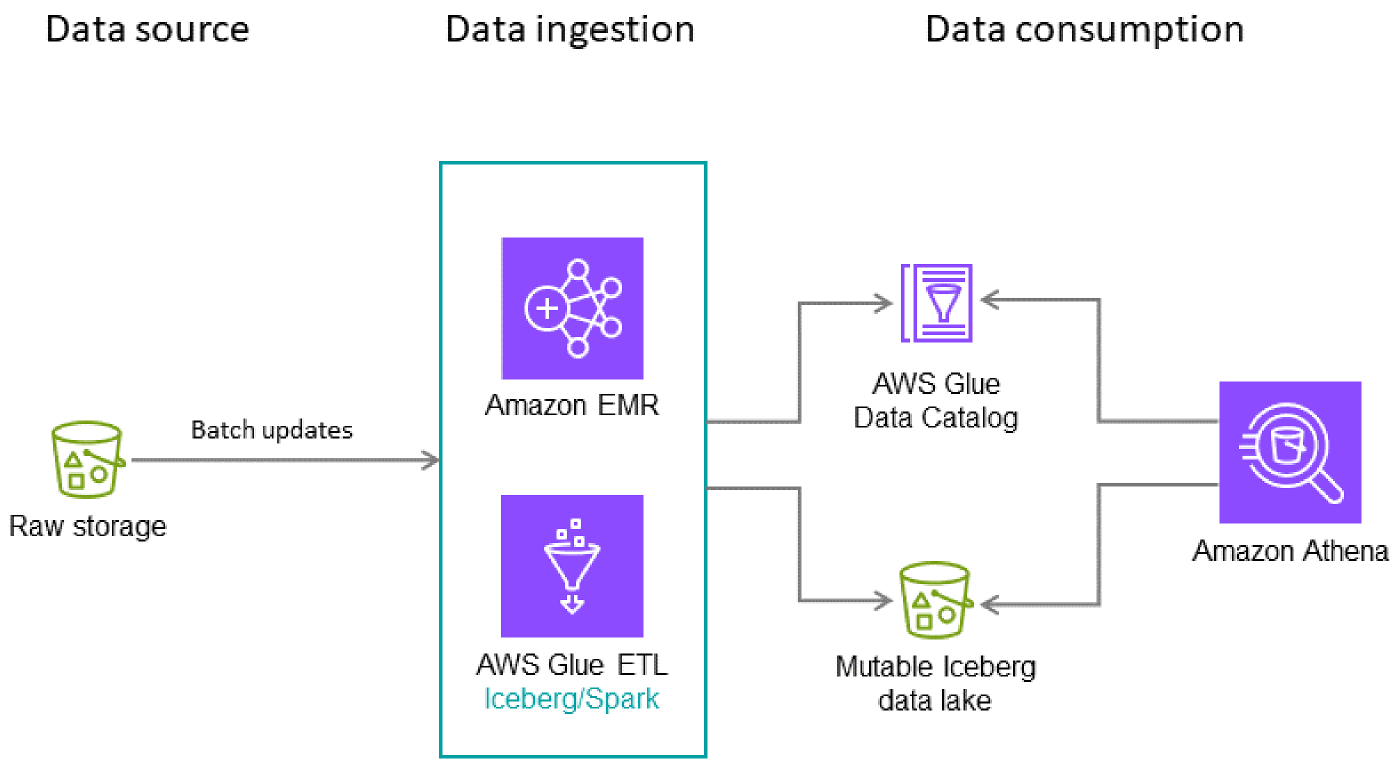
Reference architectures for Apache Iceberg on AWS

This section provides examples of how to apply best practices in different use cases such as batch ingestion and a data lake that combines batch and streaming data ingestion.

Nightly batch ingestion

For this hypothetical use case, let's say that your Iceberg table ingests credit card transactions on a nightly basis. Each batch contains only incremental updates, which must be merged into the target table. Several times per year, full historical data is received. For this scenario, we recommend the following architecture and configurations.

Note: This is just an example. The optimal configuration depends on your data and requirements.



Recommendations:

- File size: 128 MB, because Apache Spark tasks process data in 128 MB chunks.
- Write type: copy-on-write. As detailed earlier in this guide, this approach helps ensure that data is written in a read-optimized fashion.

- Partition variables: year/month/day. In our hypothetical use case, we query recent data most frequently, although we occasionally run full table scans for the past two years of data. The goal of partitioning is to drive fast read operations based on the requirements of the use case.
- Sort order: timestamp
- Data catalog: AWS Glue Data Catalog

Data lake that combines batch and near real-time ingestion

You can provision a data lake on Amazon S3 that shares batch and streaming data across accounts and Regions. For an architecture diagram and details, see the AWS blog post Build a transactional data lake using Apache Iceberg, AWS Glue, and cross-account data shares using AWS Lake Formation and Amazon Athena.

Resources

- Using the Iceberg framework in AWS Glue (AWS Glue documentation)
- Iceberg (Amazon EMR documentation)
- Using Apache Iceberg tables (Amazon Athena documentation)
- Amazon S3 documentation
- Quick Suite documentation
- Glue Catalog and Lake Formation Permissions replication (GitHub repository)
- Apache Iceberg documentation
- Apache Spark documentation

Contributors

The following people at AWS authored, co-authored, and reviewed this guide.

Contributors

- Stefano Sandona, Solutions Architect, Big Data
- Imtiaz (Taz) Sayed, Solutions Architect Tech Leader, Analytics
- Shana Schipers, Solutions Architect, Big Data
- Prashant Singh, Software Development Engineer, Amazon EMR
- Arun A K, Solutions Architect, Big Data and ETL
- Francisco Morillo, Solutions Architect, Streaming
- Suthan Phillips, Analytics Architect, Amazon EMR
- Sercan Karaoglu, Solutions Architect
- Yonatan Dolan, Analytics Specialist
- Guy Bachar, Solutions Architect
- Sofia Zilberman, Solutions Architect, Streaming
- Dan Stair, Specialist Solutions Architect
- Sakti Mishra, Solutions Architect
- Ron Ortloff, Principal Product Manager, Amazon S3
- David Zhang, Solutions Architect, Analytics

Reviewers

- Rick Sears, General Manager, Amazon EMR
- Linda OConnor, Amazon EMR Specialist
- Ian Meyers, Director, Amazon EMR
- Vinita Ananth, Director, Amazon EMR Product Management
- Jason Berkowitz, Product Manager, AWS Lake Formation
- Mahesh Mishra, Product Manager, Amazon Redshift
- Vladimir Zlatkin, Manager, Solutions Architecture, Big Data
- Karthik Prabhakar, Analytics Architect, Amazon EMR

- Vijay Jain, Product Manager
- Anupriti Warade, Product Manager, Amazon S3
- Ajit Tandale, Solutions Architect, Data
- Gwen Chen, Product Marketing Manager
- Noritaka Sekiyama, Principal Architect, Big Data

Document history

The following table describes significant changes to this guide. If you want to be notified about future updates, you can subscribe to an RSS feed.

Change	Description	Date
New section	Added information about working with Iceberg table format specification version 3.	November 26, 2025
Correction	Corrected information about `gc.enabled` settings in the snapshot procedure section.	October 24, 2025
Additions	Added new sections on working with Iceberg tables by using Trino and PyIceberg, and expanded the section on migrating tables to Iceberg.	August 12, 2025
Updates	Enhanced and clarified information throughou t the guide to reflect the latest versions of AWS Glue, Amazon EMR, and Apache Iceberg.	July 14, 2025
Additions	Added a new section on working with Iceberg tables by using Amazon Data Firehose.	February 20, 2025
Initial publication	—	April 30, 2024

AWS Prescriptive Guidance glossary

The following are commonly used terms in strategies, guides, and patterns provided by AWS Prescriptive Guidance. To suggest entries, please use the **Provide feedback** link at the end of the glossary.

Numbers

7 Rs

Seven common migration strategies for moving applications to the cloud. These strategies build upon the 5 Rs that Gartner identified in 2011 and consist of the following:

- Refactor/re-architect – Move an application and modify its architecture by taking full advantage of cloud-native features to improve agility, performance, and scalability. This typically involves porting the operating system and database. Example: Migrate your on-premises Oracle database to the Amazon Aurora PostgreSQL-Compatible Edition.
- Replatform (lift and reshape) – Move an application to the cloud, and introduce some level of optimization to take advantage of cloud capabilities. Example: Migrate your on-premises Oracle database to Amazon Relational Database Service (Amazon RDS) for Oracle in the AWS Cloud.
- Repurchase (drop and shop) – Switch to a different product, typically by moving from a traditional license to a SaaS model. Example: Migrate your customer relationship management (CRM) system to Salesforce.com.
- Rehost (lift and shift) – Move an application to the cloud without making any changes to take advantage of cloud capabilities. Example: Migrate your on-premises Oracle database to Oracle on an EC2 instance in the AWS Cloud.
- Relocate (hypervisor-level lift and shift) – Move infrastructure to the cloud without purchasing new hardware, rewriting applications, or modifying your existing operations. You migrate servers from an on-premises platform to a cloud service for the same platform. Example: Migrate a Microsoft Hyper-V application to AWS.
- Retain (revisit) – Keep applications in your source environment. These might include applications that require major refactoring, and you want to postpone that work until a later time, and legacy applications that you want to retain, because there's no business justification for migrating them.

- Retire – Decommission or remove applications that are no longer needed in your source environment.

A

ABAC

See attribute-based access control.

abstracted services

See managed services.

ACID

See atomicity, consistency, isolation, durability.

active-active migration

A database migration method in which the source and target databases are kept in sync (by using a bidirectional replication tool or dual write operations), and both databases handle transactions from connecting applications during migration. This method supports migration in small, controlled batches instead of requiring a one-time cutover. It's more flexible but requires more work than active-passive migration.

active-passive migration

A database migration method in which the source and target databases are kept in sync, but only the source database handles transactions from connecting applications while data is replicated to the target database. The target database doesn't accept any transactions during migration.

aggregate function

A SQL function that operates on a group of rows and calculates a single return value for the group. Examples of aggregate functions include `SUM` and `MAX`.

AI

See artificial intelligence.

AIOps

See artificial intelligence operations.

anonymization

The process of permanently deleting personal information in a dataset. Anonymization can help protect personal privacy. Anonymized data is no longer considered to be personal data.

anti-pattern

A frequently used solution for a recurring issue where the solution is counter-productive, ineffective, or less effective than an alternative.

application control

A security approach that allows the use of only approved applications in order to help protect a system from malware.

application portfolio

A collection of detailed information about each application used by an organization, including the cost to build and maintain the application, and its business value. This information is key to the portfolio discovery and analysis process and helps identify and prioritize the applications to be migrated, modernized, and optimized.

artificial intelligence (AI)

The field of computer science that is dedicated to using computing technologies to perform cognitive functions that are typically associated with humans, such as learning, solving problems, and recognizing patterns. For more information, see What is Artificial Intelligence?

artificial intelligence operations (AIOps)

The process of using machine learning techniques to solve operational problems, reduce operational incidents and human intervention, and increase service quality. For more information about how AIOps is used in the AWS migration strategy, see the operations integration guide.

asymmetric encryption

An encryption algorithm that uses a pair of keys, a public key for encryption and a private key for decryption. You can share the public key because it isn't used for decryption, but access to the private key should be highly restricted.

atomicity, consistency, isolation, durability (ACID)

A set of software properties that guarantee the data validity and operational reliability of a database, even in the case of errors, power failures, or other problems.

attribute-based access control (ABAC)

The practice of creating fine-grained permissions based on user attributes, such as department, job role, and team name. For more information, see ABAC for AWS in the AWS Identity and Access Management (IAM) documentation.

authoritative data source

A location where you store the primary version of data, which is considered to be the most reliable source of information. You can copy data from the authoritative data source to other locations for the purposes of processing or modifying the data, such as anonymizing, redacting, or pseudonymizing it.

Availability Zone

A distinct location within an AWS Region that is insulated from failures in other Availability Zones and provides inexpensive, low-latency network connectivity to other Availability Zones in the same Region.

AWS Cloud Adoption Framework (AWS CAF)

A framework of guidelines and best practices from AWS to help organizations develop an efficient and effective plan to move successfully to the cloud. AWS CAF organizes guidance into six focus areas called perspectives: business, people, governance, platform, security, and operations. The business, people, and governance perspectives focus on business skills and processes; the platform, security, and operations perspectives focus on technical skills and processes. For example, the people perspective targets stakeholders who handle human resources (HR), staffing functions, and people management. For this perspective, AWS CAF provides guidance for people development, training, and communications to help ready the organization for successful cloud adoption. For more information, see the AWS CAF website and the AWS CAF whitepaper.

AWS Workload Qualification Framework (AWS WQF)

A tool that evaluates database migration workloads, recommends migration strategies, and provides work estimates. AWS WQF is included with AWS Schema Conversion Tool (AWS SCT). It analyzes database schemas and code objects, application code, dependencies, and performance characteristics, and provides assessment reports.

B

bad bot

A bot that is intended to disrupt or cause harm to individuals or organizations.

BCP

See business continuity planning.

behavior graph

A unified, interactive view of resource behavior and interactions over time. You can use a behavior graph with Amazon Detective to examine failed logon attempts, suspicious API calls, and similar actions. For more information, see Data in a behavior graph in the Detective documentation.

big-endian system

A system that stores the most significant byte first. See also endianness.

binary classification

A process that predicts a binary outcome (one of two possible classes). For example, your ML model might need to predict problems such as “Is this email spam or not spam?" or "Is this product a book or a car?"

bloom filter

A probabilistic, memory-efficient data structure that is used to test whether an element is a member of a set.

blue/green deployment

A deployment strategy where you create two separate but identical environments. You run the current application version in one environment (blue) and the new application version in the other environment (green). This strategy helps you quickly roll back with minimal impact.

bot

A software application that runs automated tasks over the internet and simulates human activity or interaction. Some bots are useful or beneficial, such as web crawlers that index information on the internet. Some other bots, known as *bad bots*, are intended to disrupt or cause harm to individuals or organizations.

botnet

Networks of bots that are infected by malware and are under the control of a single party, known as a *bot herder* or *bot operator*. Botnets are the best-known mechanism to scale bots and their impact.

branch

A contained area of a code repository. The first branch created in a repository is the *main branch*. You can create a new branch from an existing branch, and you can then develop features or fix bugs in the new branch. A branch you create to build a feature is commonly referred to as a *feature branch*. When the feature is ready for release, you merge the feature branch back into the main branch. For more information, see About branches (GitHub documentation).

break-glass access

In exceptional circumstances and through an approved process, a quick means for a user to gain access to an AWS account that they don't typically have permissions to access. For more information, see the Implement break-glass procedures indicator in the AWS Well-Architected guidance.

brownfield strategy

The existing infrastructure in your environment. When adopting a brownfield strategy for a system architecture, you design the architecture around the constraints of the current systems and infrastructure. If you are expanding the existing infrastructure, you might blend brownfield and greenfield strategies.

buffer cache

The memory area where the most frequently accessed data is stored.

business capability

What a business does to generate value (for example, sales, customer service, or marketing). Microservices architectures and development decisions can be driven by business capabilities. For more information, see the Organized around business capabilities section of the Running containerized microservices on AWS whitepaper.

business continuity planning (BCP)

A plan that addresses the potential impact of a disruptive event, such as a large-scale migration, on operations and enables a business to resume operations quickly.

C

CAF

See AWS Cloud Adoption Framework.

canary deployment

The slow and incremental release of a version to end users. When you are confident, you deploy the new version and replace the current version in its entirety.

CCoE

See Cloud Center of Excellence.

CDC

See change data capture.

change data capture (CDC)

The process of tracking changes to a data source, such as a database table, and recording metadata about the change. You can use CDC for various purposes, such as auditing or replicating changes in a target system to maintain synchronization.

chaos engineering

Intentionally introducing failures or disruptive events to test a system's resilience. You can use AWS Fault Injection Service (AWS FIS) to perform experiments that stress your AWS workloads and evaluate their response.

CI/CD

See continuous integration and continuous delivery.

classification

A categorization process that helps generate predictions. ML models for classification problems predict a discrete value. Discrete values are always distinct from one another. For example, a model might need to evaluate whether or not there is a car in an image.

client-side encryption

Encryption of data locally, before the target AWS service receives it.

Cloud Center of Excellence (CCoE)

A multi-disciplinary team that drives cloud adoption efforts across an organization, including developing cloud best practices, mobilizing resources, establishing migration timelines, and leading the organization through large-scale transformations. For more information, see the CCoE posts on the AWS Cloud Enterprise Strategy Blog.

cloud computing

The cloud technology that is typically used for remote data storage and IoT device management. Cloud computing is commonly connected to edge computing technology.

cloud operating model

In an IT organization, the operating model that is used to build, mature, and optimize one or more cloud environments. For more information, see Building your Cloud Operating Model.

cloud stages of adoption

The four phases that organizations typically go through when they migrate to the AWS Cloud:

- Project – Running a few cloud-related projects for proof of concept and learning purposes
- Foundation – Making foundational investments to scale your cloud adoption (e.g., creating a landing zone, defining a CCoE, establishing an operations model)
- Migration – Migrating individual applications
- Re-invention – Optimizing products and services, and innovating in the cloud

These stages were defined by Stephen Orban in the blog post The Journey Toward Cloud-First & the Stages of Adoption on the AWS Cloud Enterprise Strategy blog. For information about how they relate to the AWS migration strategy, see the migration readiness guide.

CMDB

See configuration management database.

code repository

A location where source code and other assets, such as documentation, samples, and scripts, are stored and updated through version control processes. Common cloud repositories include GitHub or Bitbucket Cloud. Each version of the code is called a *branch*. In a microservice structure, each repository is devoted to a single piece of functionality. A single CI/CD pipeline can use multiple repositories.

cold cache

A buffer cache that is empty, not well populated, or contains stale or irrelevant data. This affects performance because the database instance must read from the main memory or disk, which is slower than reading from the buffer cache.

cold data

Data that is rarely accessed and is typically historical. When querying this kind of data, slow queries are typically acceptable. Moving this data to lower-performing and less expensive storage tiers or classes can reduce costs.

computer vision (CV)

A field of AI that uses machine learning to analyze and extract information from visual formats such as digital images and videos. For example, Amazon SageMaker AI provides image processing algorithms for CV.

configuration drift

For a workload, a configuration change from the expected state. It might cause the workload to become noncompliant, and it's typically gradual and unintentional.

configuration management database (CMDB)

A repository that stores and manages information about a database and its IT environment, including both hardware and software components and their configurations. You typically use data from a CMDB in the portfolio discovery and analysis stage of migration.

conformance pack

A collection of AWS Config rules and remediation actions that you can assemble to customize your compliance and security checks. You can deploy a conformance pack as a single entity in an AWS account and Region, or across an organization, by using a YAML template. For more information, see Conformance packs in the AWS Config documentation.

continuous integration and continuous delivery (CI/CD)

The process of automating the source, build, test, staging, and production stages of the software release process. CI/CD is commonly described as a pipeline. CI/CD can help you automate processes, improve productivity, improve code quality, and deliver faster. For more information, see Benefits of continuous delivery. CD can also stand for *continuous deployment*. For more information, see Continuous Delivery vs. Continuous Deployment.

CV

See computer vision.

D

data at rest

Data that is stationary in your network, such as data that is in storage.

data classification

A process for identifying and categorizing the data in your network based on its criticality and sensitivity. It is a critical component of any cybersecurity risk management strategy because it helps you determine the appropriate protection and retention controls for the data. Data classification is a component of the security pillar in the AWS Well-Architected Framework. For more information, see Data classification.

data drift

A meaningful variation between the production data and the data that was used to train an ML model, or a meaningful change in the input data over time. Data drift can reduce the overall quality, accuracy, and fairness in ML model predictions.

data in transit

Data that is actively moving through your network, such as between network resources.

data mesh

An architectural framework that provides distributed, decentralized data ownership with centralized management and governance.

data minimization

The principle of collecting and processing only the data that is strictly necessary. Practicing data minimization in the AWS Cloud can reduce privacy risks, costs, and your analytics carbon footprint.

data perimeter

A set of preventive guardrails in your AWS environment that help make sure that only trusted identities are accessing trusted resources from expected networks. For more information, see Building a data perimeter on AWS.

data preprocessing

To transform raw data into a format that is easily parsed by your ML model. Preprocessing data can mean removing certain columns or rows and addressing missing, inconsistent, or duplicate values.

data provenance

The process of tracking the origin and history of data throughout its lifecycle, such as how the data was generated, transmitted, and stored.

data subject

An individual whose data is being collected and processed.

data warehouse

A data management system that supports business intelligence, such as analytics. Data warehouses commonly contain large amounts of historical data, and they are typically used for queries and analysis.

database definition language (DDL)

Statements or commands for creating or modifying the structure of tables and objects in a database.

database manipulation language (DML)

Statements or commands for modifying (inserting, updating, and deleting) information in a database.

DDL

See database definition language.

deep ensemble

To combine multiple deep learning models for prediction. You can use deep ensembles to obtain a more accurate prediction or for estimating uncertainty in predictions.

deep learning

An ML subfield that uses multiple layers of artificial neural networks to identify mapping between input data and target variables of interest.

defense-in-depth

An information security approach in which a series of security mechanisms and controls are thoughtfully layered throughout a computer network to protect the confidentiality, integrity, and availability of the network and the data within. When you adopt this strategy on AWS, you add multiple controls at different layers of the AWS Organizations structure to help secure resources. For example, a defense-in-depth approach might combine multi-factor authentication, network segmentation, and encryption.

delegated administrator

In AWS Organizations, a compatible service can register an AWS member account to administer the organization’s accounts and manage permissions for that service. This account is called the *delegated administrator* for that service. For more information and a list of compatible services, see Services that work with AWS Organizations in the AWS Organizations documentation.

deployment

The process of making an application, new features, or code fixes available in the target environment. Deployment involves implementing changes in a code base and then building and running that code base in the application’s environments.

development environment

See environment.

detective control

A security control that is designed to detect, log, and alert after an event has occurred. These controls are a second line of defense, alerting you to security events that bypassed the preventative controls in place. For more information, see Detective controls in *Implementing security controls on AWS*.

development value stream mapping (DVSM)

A process used to identify and prioritize constraints that adversely affect speed and quality in a software development lifecycle. DVSM extends the value stream mapping process originally designed for lean manufacturing practices. It focuses on the steps and teams required to create and move value through the software development process.

digital twin

A virtual representation of a real-world system, such as a building, factory, industrial equipment, or production line. Digital twins support predictive maintenance, remote monitoring, and production optimization.

dimension table

In a star schema, a smaller table that contains data attributes about quantitative data in a fact table. Dimension table attributes are typically text fields or discrete numbers that behave like text. These attributes are commonly used for query constraining, filtering, and result set labeling.

disaster

An event that prevents a workload or system from fulfilling its business objectives in its primary deployed location. These events can be natural disasters, technical failures, or the result of human actions, such as unintentional misconfiguration or a malware attack.

disaster recovery (DR)

The strategy and process you use to minimize downtime and data loss caused by a disaster. For more information, see Disaster Recovery of Workloads on AWS: Recovery in the Cloud in the AWS Well-Architected Framework.

DML

See database manipulation language.

domain-driven design

An approach to developing a complex software system by connecting its components to evolving domains, or core business goals, that each component serves. This concept was introduced by Eric Evans in his book, *Domain-Driven Design: Tackling Complexity in the Heart of Software* (Boston: Addison-Wesley Professional, 2003). For information about how you can use domain-driven design with the strangler fig pattern, see Modernizing legacy Microsoft ASP.NET (ASMX) web services incrementally by using containers and Amazon API Gateway.

DR

See disaster recovery.

drift detection

Tracking deviations from a baselined configuration. For example, you can use AWS CloudFormation to detect drift in system resources, or you can use AWS Control Tower to detect changes in your landing zone that might affect compliance with governance requirements.

DVSM

See development value stream mapping.

E

EDA

See exploratory data analysis.

EDI

See electronic data interchange.

edge computing

The technology that increases the computing power for smart devices at the edges of an IoT network. When compared with cloud computing, edge computing can reduce communication latency and improve response time.

electronic data interchange (EDI)

The automated exchange of business documents between organizations. For more information, see What is Electronic Data Interchange.

encryption

A computing process that transforms plaintext data, which is human-readable, into ciphertext.

encryption key

A cryptographic string of randomized bits that is generated by an encryption algorithm. Keys can vary in length, and each key is designed to be unpredictable and unique.

endianness

The order in which bytes are stored in computer memory. Big-endian systems store the most significant byte first. Little-endian systems store the least significant byte first.

endpoint

See service endpoint.

endpoint service

A service that you can host in a virtual private cloud (VPC) to share with other users. You can create an endpoint service with AWS PrivateLink and grant permissions to other AWS accounts or to AWS Identity and Access Management (IAM) principals. These accounts or principals can connect to your endpoint service privately by creating interface VPC endpoints. For more information, see Create an endpoint service in the Amazon Virtual Private Cloud (Amazon VPC) documentation.

enterprise resource planning (ERP)

A system that automates and manages key business processes (such as accounting, MES, and project management) for an enterprise.

envelope encryption

The process of encrypting an encryption key with another encryption key. For more information, see Envelope encryption in the AWS Key Management Service (AWS KMS) documentation.

environment

An instance of a running application. The following are common types of environments in cloud computing:

- development environment – An instance of a running application that is available only to the core team responsible for maintaining the application. Development environments are used to test changes before promoting them to upper environments. This type of environment is sometimes referred to as a *test environment*.
- lower environments – All development environments for an application, such as those used for initial builds and tests.
- production environment – An instance of a running application that end users can access. In a CI/CD pipeline, the production environment is the last deployment environment.
- upper environments – All environments that can be accessed by users other than the core development team. This can include a production environment, preproduction environments, and environments for user acceptance testing.

epic

In agile methodologies, functional categories that help organize and prioritize your work. Epics provide a high-level description of requirements and implementation tasks. For example, AWS CAF security epics include identity and access management, detective controls, infrastructure security, data protection, and incident response. For more information about epics in the AWS migration strategy, see the program implementation guide.

ERP

See enterprise resource planning.

exploratory data analysis (EDA)

The process of analyzing a dataset to understand its main characteristics. You collect or aggregate data and then perform initial investigations to find patterns, detect anomalies, and check assumptions. EDA is performed by calculating summary statistics and creating data visualizations.

F

fact table

The central table in a star schema. It stores quantitative data about business operations. Typically, a fact table contains two types of columns: those that contain measures and those that contain a foreign key to a dimension table.

fail fast

A philosophy that uses frequent and incremental testing to reduce the development lifecycle. It is a critical part of an agile approach.

fault isolation boundary

In the AWS Cloud, a boundary such as an Availability Zone, AWS Region, control plane, or data plane that limits the effect of a failure and helps improve the resilience of workloads. For more information, see AWS Fault Isolation Boundaries.

feature branch

See branch.

features

The input data that you use to make a prediction. For example, in a manufacturing context, features could be images that are periodically captured from the manufacturing line.

feature importance

How significant a feature is for a model's predictions. This is usually expressed as a numerical score that can be calculated through various techniques, such as Shapley Additive Explanations (SHAP) and integrated gradients. For more information, see Machine learning model interpretability with AWS.

feature transformation

To optimize data for the ML process, including enriching data with additional sources, scaling values, or extracting multiple sets of information from a single data field. This enables the ML model to benefit from the data. For example, if you break down the “2021-05-27 00:15:37” date into “2021”, “May”, “Thu”, and “15”, you can help the learning algorithm learn nuanced patterns associated with different data components.

few-shot prompting

Providing an LLM with a small number of examples that demonstrate the task and desired output before asking it to perform a similar task. This technique is an application of in-context learning, where models learn from examples (*shots*) that are embedded in prompts. Few-shot prompting can be effective for tasks that require specific formatting, reasoning, or domain knowledge. See also zero-shot prompting.

FGAC

See fine-grained access control.

fine-grained access control (FGAC)

The use of multiple conditions to allow or deny an access request.

flash-cut migration

A database migration method that uses continuous data replication through change data capture to migrate data in the shortest time possible, instead of using a phased approach. The objective is to keep downtime to a minimum.

FM

See foundation model.

foundation model (FM)

A large deep-learning neural network that has been training on massive datasets of generalized and unlabeled data. FMs are capable of performing a wide variety of general tasks, such as understanding language, generating text and images, and conversing in natural language. For more information, see What are Foundation Models.

G

generative AI

A subset of AI models that have been trained on large amounts of data and that can use a simple text prompt to create new content and artifacts, such as images, videos, text, and audio. For more information, see What is Generative AI.

geo blocking

See geographic restrictions.

geographic restrictions (geo blocking)

In Amazon CloudFront, an option to prevent users in specific countries from accessing content distributions. You can use an allow list or block list to specify approved and banned countries. For more information, see Restricting the geographic distribution of your content in the CloudFront documentation.

Gitflow workflow

An approach in which lower and upper environments use different branches in a source code repository. The Gitflow workflow is considered legacy, and the trunk-based workflow is the modern, preferred approach.

golden image

A snapshot of a system or software that is used as a template to deploy new instances of that system or software. For example, in manufacturing, a golden image can be used to provision software on multiple devices and helps improve speed, scalability, and productivity in device manufacturing operations.

greenfield strategy

The absence of existing infrastructure in a new environment. When adopting a greenfield strategy for a system architecture, you can select all new technologies without the restriction of compatibility with existing infrastructure, also known as brownfield. If you are expanding the existing infrastructure, you might blend brownfield and greenfield strategies.

guardrail

A high-level rule that helps govern resources, policies, and compliance across organizational units (OUs). *Preventive guardrails* enforce policies to ensure alignment to compliance standards. They are implemented by using service control policies and IAM permissions boundaries.

Detective guardrails detect policy violations and compliance issues, and generate alerts for remediation. They are implemented by using AWS Config, AWS Security Hub CSPM, Amazon GuardDuty, AWS Trusted Advisor, Amazon Inspector, and custom AWS Lambda checks.

H

HA

See high availability.

heterogeneous database migration

Migrating your source database to a target database that uses a different database engine (for example, Oracle to Amazon Aurora). Heterogeneous migration is typically part of a re-architecting effort, and converting the schema can be a complex task. AWS provides AWS SCT that helps with schema conversions.

high availability (HA)

The ability of a workload to operate continuously, without intervention, in the event of challenges or disasters. HA systems are designed to automatically fail over, consistently deliver high-quality performance, and handle different loads and failures with minimal performance impact.

historian modernization

An approach used to modernize and upgrade operational technology (OT) systems to better serve the needs of the manufacturing industry. A *historian* is a type of database that is used to collect and store data from various sources in a factory.

holdout data

A portion of historical, labeled data that is withheld from a dataset that is used to train a machine learning model. You can use holdout data to evaluate the model performance by comparing the model predictions against the holdout data.

homogeneous database migration

Migrating your source database to a target database that shares the same database engine (for example, Microsoft SQL Server to Amazon RDS for SQL Server). Homogeneous migration is typically part of a rehosting or replatforming effort. You can use native database utilities to migrate the schema.

hot data

Data that is frequently accessed, such as real-time data or recent translational data. This data typically requires a high-performance storage tier or class to provide fast query responses.

hotfix

An urgent fix for a critical issue in a production environment. Due to its urgency, a hotfix is usually made outside of the typical DevOps release workflow.

hypercare period

Immediately following cutover, the period of time when a migration team manages and monitors the migrated applications in the cloud in order to address any issues. Typically, this period is 1–4 days in length. At the end of the hypercare period, the migration team typically transfers responsibility for the applications to the cloud operations team.

I

IaC

See infrastructure as code.

identity-based policy

A policy attached to one or more IAM principals that defines their permissions within the AWS Cloud environment.

idle application

An application that has an average CPU and memory usage between 5 and 20 percent over a period of 90 days. In a migration project, it is common to retire these applications or retain them on premises.

IIoT

See industrial Internet of Things.

immutable infrastructure

A model that deploys new infrastructure for production workloads instead of updating, patching, or modifying the existing infrastructure. Immutable infrastructures are inherently more consistent, reliable, and predictable than mutable infrastructure. For more information, see the Deploy using immutable infrastructure best practice in the AWS Well-Architected Framework.

inbound (ingress) VPC

In an AWS multi-account architecture, a VPC that accepts, inspects, and routes network connections from outside an application. The AWS Security Reference Architecture recommends setting up your Network account with inbound, outbound, and inspection VPCs to protect the two-way interface between your application and the broader internet.

incremental migration

A cutover strategy in which you migrate your application in small parts instead of performing a single, full cutover. For example, you might move only a few microservices or users to the new system initially. After you verify that everything is working properly, you can incrementally move additional microservices or users until you can decommission your legacy system. This strategy reduces the risks associated with large migrations.

Industry 4.0

A term that was introduced by Klaus Schwab in 2016 to refer to the modernization of manufacturing processes through advances in connectivity, real-time data, automation, analytics, and AI/ML.

infrastructure

All of the resources and assets contained within an application's environment.

infrastructure as code (IaC)

The process of provisioning and managing an application's infrastructure through a set of configuration files. IaC is designed to help you centralize infrastructure management, standardize resources, and scale quickly so that new environments are repeatable, reliable, and consistent.

industrial Internet of Things (IIoT)

The use of internet-connected sensors and devices in the industrial sectors, such as manufacturing, energy, automotive, healthcare, life sciences, and agriculture. For more information, see Building an industrial Internet of Things (IIoT) digital transformation strategy.

inspection VPC

In an AWS multi-account architecture, a centralized VPC that manages inspections of network traffic between VPCs (in the same or different AWS Regions), the internet, and on-premises networks. The AWS Security Reference Architecture recommends setting up your Network account with inbound, outbound, and inspection VPCs to protect the two-way interface between your application and the broader internet.

Internet of Things (IoT)

The network of connected physical objects with embedded sensors or processors that communicate with other devices and systems through the internet or over a local communication network. For more information, see What is IoT?

interpretability

A characteristic of a machine learning model that describes the degree to which a human can understand how the model's predictions depend on its inputs. For more information, see Machine learning model interpretability with AWS.

IoT

See Internet of Things.

IT information library (ITIL)

A set of best practices for delivering IT services and aligning these services with business requirements. ITIL provides the foundation for ITSM.

IT service management (ITSM)

Activities associated with designing, implementing, managing, and supporting IT services for an organization. For information about integrating cloud operations with ITSM tools, see the operations integration guide.

ITIL

See IT information library.

ITSM

See IT service management.

L

label-based access control (LBAC)

An implementation of mandatory access control (MAC) where the users and the data itself are each explicitly assigned a security label value. The intersection between the user security label and data security label determines which rows and columns can be seen by the user.

landing zone

A landing zone is a well-architected, multi-account AWS environment that is scalable and secure. This is a starting point from which your organizations can quickly launch and deploy workloads and applications with confidence in their security and infrastructure environment. For more information about landing zones, see Setting up a secure and scalable multi-account AWS environment.

large language model (LLM)

A deep learning AI model that is pretrained on a vast amount of data. An LLM can perform multiple tasks, such as answering questions, summarizing documents, translating text into other languages, and completing sentences. For more information, see What are LLMs.

large migration

A migration of 300 or more servers.

LBAC

See label-based access control.

least privilege

The security best practice of granting the minimum permissions required to perform a task. For more information, see Apply least-privilege permissions in the IAM documentation.

lift and shift

See 7 Rs.

little-endian system

A system that stores the least significant byte first. See also endianness.

LLM

See large language model.

lower environments

See environment.

M

machine learning (ML)

A type of artificial intelligence that uses algorithms and techniques for pattern recognition and learning. ML analyzes and learns from recorded data, such as Internet of Things (IoT) data, to generate a statistical model based on patterns. For more information, see Machine Learning.

main branch

See branch.

malware

Software that is designed to compromise computer security or privacy. Malware might disrupt computer systems, leak sensitive information, or gain unauthorized access. Examples of malware include viruses, worms, ransomware, Trojan horses, spyware, and keyloggers.

managed services

AWS services for which AWS operates the infrastructure layer, the operating system, and platforms, and you access the endpoints to store and retrieve data. Amazon Simple Storage Service (Amazon S3) and Amazon DynamoDB are examples of managed services. These are also known as *abstracted services*.

manufacturing execution system (MES)

A software system for tracking, monitoring, documenting, and controlling production processes that convert raw materials to finished products on the shop floor.

MAP

See Migration Acceleration Program.

mechanism

A complete process in which you create a tool, drive adoption of the tool, and then inspect the results in order to make adjustments. A mechanism is a cycle that reinforces and improves itself as it operates. For more information, see Building mechanisms in the AWS Well-Architected Framework.

member account

All AWS accounts other than the management account that are part of an organization in AWS Organizations. An account can be a member of only one organization at a time.

MES

See manufacturing execution system.

Message Queuing Telemetry Transport (MQTT)

A lightweight, machine-to-machine (M2M) communication protocol, based on the publish/subscribe pattern, for resource-constrained IoT devices.

microservice

A small, independent service that communicates over well-defined APIs and is typically owned by small, self-contained teams. For example, an insurance system might include microservices that map to business capabilities, such as sales or marketing, or subdomains, such as purchasing, claims, or analytics. The benefits of microservices include agility, flexible scaling, easy deployment, reusable code, and resilience. For more information, see Integrating microservices by using AWS serverless services.

microservices architecture

An approach to building an application with independent components that run each application process as a microservice. These microservices communicate through a well-defined interface by using lightweight APIs. Each microservice in this architecture can be updated, deployed, and scaled to meet demand for specific functions of an application. For more information, see Implementing microservices on AWS.

Migration Acceleration Program (MAP)

An AWS program that provides consulting support, training, and services to help organizations build a strong operational foundation for moving to the cloud, and to help offset the initial cost of migrations. MAP includes a migration methodology for executing legacy migrations in a methodical way and a set of tools to automate and accelerate common migration scenarios.

migration at scale

The process of moving the majority of the application portfolio to the cloud in waves, with more applications moved at a faster rate in each wave. This phase uses the best practices and lessons learned from the earlier phases to implement a *migration factory* of teams, tools, and processes to streamline the migration of workloads through automation and agile delivery. This is the third phase of the AWS migration strategy.

migration factory

Cross-functional teams that streamline the migration of workloads through automated, agile approaches. Migration factory teams typically include operations, business analysts and owners, migration engineers, developers, and DevOps professionals working in sprints. Between 20 and 50 percent of an enterprise application portfolio consists of repeated patterns that can be optimized by a factory approach. For more information, see the discussion of migration factories and the Cloud Migration Factory guide in this content set.

migration metadata

The information about the application and server that is needed to complete the migration. Each migration pattern requires a different set of migration metadata. Examples of migration metadata include the target subnet, security group, and AWS account.

migration pattern

A repeatable migration task that details the migration strategy, the migration destination, and the migration application or service used. Example: Rehost migration to Amazon EC2 with AWS Application Migration Service.

Migration Portfolio Assessment (MPA)

An online tool that provides information for validating the business case for migrating to the AWS Cloud. MPA provides detailed portfolio assessment (server right-sizing, pricing, TCO comparisons, migration cost analysis) as well as migration planning (application data analysis and data collection, application grouping, migration prioritization, and wave planning). The MPA tool (requires login) is available free of charge to all AWS consultants and APN Partner consultants.

Migration Readiness Assessment (MRA)

The process of gaining insights about an organization's cloud readiness status, identifying strengths and weaknesses, and building an action plan to close identified gaps, using the AWS CAF. For more information, see the migration readiness guide. MRA is the first phase of the AWS migration strategy.

migration strategy

The approach used to migrate a workload to the AWS Cloud. For more information, see the 7 Rs entry in this glossary and see Mobilize your organization to accelerate large-scale migrations.

ML

See machine learning.

modernization

Transforming an outdated (legacy or monolithic) application and its infrastructure into an agile, elastic, and highly available system in the cloud to reduce costs, gain efficiencies, and take advantage of innovations. For more information, see Strategy for modernizing applications in the AWS Cloud.

modernization readiness assessment

An evaluation that helps determine the modernization readiness of an organization's applications; identifies benefits, risks, and dependencies; and determines how well the organization can support the future state of those applications. The outcome of the assessment is a blueprint of the target architecture, a roadmap that details development phases and milestones for the modernization process, and an action plan for addressing identified gaps. For more information, see Evaluating modernization readiness for applications in the AWS Cloud.

monolithic applications (monoliths)

Applications that run as a single service with tightly coupled processes. Monolithic applications have several drawbacks. If one application feature experiences a spike in demand, the entire architecture must be scaled. Adding or improving a monolithic application's features also becomes more complex when the code base grows. To address these issues, you can use a microservices architecture. For more information, see Decomposing monoliths into microservices.

MPA

See Migration Portfolio Assessment.

MQTT

See Message Queuing Telemetry Transport.

multiclass classification

A process that helps generate predictions for multiple classes (predicting one of more than two outcomes). For example, an ML model might ask "Is this product a book, car, or phone?" or "Which product category is most interesting to this customer?"

mutable infrastructure

A model that updates and modifies the existing infrastructure for production workloads. For improved consistency, reliability, and predictability, the AWS Well-Architected Framework recommends the use of immutable infrastructure as a best practice.

O

OAC

See origin access control.

OAI

See origin access identity.

OCM

See organizational change management.

offline migration

A migration method in which the source workload is taken down during the migration process. This method involves extended downtime and is typically used for small, non-critical workloads.

OI

See operations integration.

OLA

See operational-level agreement.

online migration

A migration method in which the source workload is copied to the target system without being taken offline. Applications that are connected to the workload can continue to function during the migration. This method involves zero to minimal downtime and is typically used for critical production workloads.

OPC-UA

See Open Process Communications - Unified Architecture.

Open Process Communications - Unified Architecture (OPC-UA)

A machine-to-machine (M2M) communication protocol for industrial automation. OPC-UA provides an interoperability standard with data encryption, authentication, and authorization schemes.

operational-level agreement (OLA)

An agreement that clarifies what functional IT groups promise to deliver to each other, to support a service-level agreement (SLA).

operational readiness review (ORR)

A checklist of questions and associated best practices that help you understand, evaluate, prevent, or reduce the scope of incidents and possible failures. For more information, see Operational Readiness Reviews (ORR) in the AWS Well-Architected Framework.

operational technology (OT)

Hardware and software systems that work with the physical environment to control industrial operations, equipment, and infrastructure. In manufacturing, the integration of OT and information technology (IT) systems is a key focus for Industry 4.0 transformations.

operations integration (OI)

The process of modernizing operations in the cloud, which involves readiness planning, automation, and integration. For more information, see the operations integration guide.

organization trail

A trail that's created by AWS CloudTrail that logs all events for all AWS accounts in an organization in AWS Organizations. This trail is created in each AWS account that's part of the organization and tracks the activity in each account. For more information, see Creating a trail for an organization in the CloudTrail documentation.

organizational change management (OCM)

A framework for managing major, disruptive business transformations from a people, culture, and leadership perspective. OCM helps organizations prepare for, and transition to, new systems and strategies by accelerating change adoption, addressing transitional issues, and driving cultural and organizational changes. In the AWS migration strategy, this framework is called *people acceleration*, because of the speed of change required in cloud adoption projects. For more information, see the OCM guide.

origin access control (OAC)

In CloudFront, an enhanced option for restricting access to secure your Amazon Simple Storage Service (Amazon S3) content. OAC supports all S3 buckets in all AWS Regions, server-side encryption with AWS KMS (SSE-KMS), and dynamic `PUT` and `DELETE` requests to the S3 bucket.

origin access identity (OAI)

In CloudFront, an option for restricting access to secure your Amazon S3 content. When you use OAI, CloudFront creates a principal that Amazon S3 can authenticate with. Authenticated principals can access content in an S3 bucket only through a specific CloudFront distribution. See also OAC, which provides more granular and enhanced access control.

ORR

See operational readiness review.

OT

See operational technology.

outbound (egress) VPC

In an AWS multi-account architecture, a VPC that handles network connections that are initiated from within an application. The AWS Security Reference Architecture recommends setting up your Network account with inbound, outbound, and inspection VPCs to protect the two-way interface between your application and the broader internet.

P

permissions boundary

An IAM management policy that is attached to IAM principals to set the maximum permissions that the user or role can have. For more information, see Permissions boundaries in the IAM documentation.

personally identifiable information (PII)

Information that, when viewed directly or paired with other related data, can be used to reasonably infer the identity of an individual. Examples of PII include names, addresses, and contact information.

PII

See personally identifiable information.

playbook

A set of predefined steps that capture the work associated with migrations, such as delivering core operations functions in the cloud. A playbook can take the form of scripts, automated runbooks, or a summary of processes or steps required to operate your modernized environment.

PLC

See programmable logic controller.

PLM

See product lifecycle management.

policy

An object that can define permissions (see identity-based policy), specify access conditions (see resource-based policy), or define the maximum permissions for all accounts in an organization in AWS Organizations (see service control policy).

polyglot persistence

Independently choosing a microservice's data storage technology based on data access patterns and other requirements. If your microservices have the same data storage technology, they can encounter implementation challenges or experience poor performance. Microservices are more easily implemented and achieve better performance and scalability if they use the data store best adapted to their requirements. For more information, see Enabling data persistence in microservices.

portfolio assessment

A process of discovering, analyzing, and prioritizing the application portfolio in order to plan the migration. For more information, see Evaluating migration readiness.

predicate

A query condition that returns `true` or `false`, commonly located in a `WHERE` clause.

predicate pushdown

A database query optimization technique that filters the data in the query before transfer. This reduces the amount of data that must be retrieved and processed from the relational database, and it improves query performance.

preventative control

A security control that is designed to prevent an event from occurring. These controls are a first line of defense to help prevent unauthorized access or unwanted changes to your network. For more information, see Preventative controls in *Implementing security controls on AWS*.

principal

An entity in AWS that can perform actions and access resources. This entity is typically a root user for an AWS account, an IAM role, or a user. For more information, see *Principal* in Roles terms and concepts in the IAM documentation.

privacy by design

A system engineering approach that takes privacy into account through the whole development process.

private hosted zones

A container that holds information about how you want Amazon Route 53 to respond to DNS queries for a domain and its subdomains within one or more VPCs. For more information, see Working with private hosted zones in the Route 53 documentation.

proactive control

A security control designed to prevent the deployment of noncompliant resources. These controls scan resources before they are provisioned. If the resource is not compliant with the control, then it isn't provisioned. For more information, see the Controls reference guide in the AWS Control Tower documentation and see Proactive controls in *Implementing security controls on AWS*.

product lifecycle management (PLM)

The management of data and processes for a product throughout its entire lifecycle, from design, development, and launch, through growth and maturity, to decline and removal.

production environment

See environment.

programmable logic controller (PLC)

In manufacturing, a highly reliable, adaptable computer that monitors machines and automates manufacturing processes.

prompt chaining

Using the output of one LLM prompt as the input for the next prompt to generate better responses. This technique is used to break down a complex task into subtasks, or to iteratively refine or expand a preliminary response. It helps improve the accuracy and relevance of a model's responses and allows for more granular, personalized results.

pseudonymization

The process of replacing personal identifiers in a dataset with placeholder values. Pseudonymization can help protect personal privacy. Pseudonymized data is still considered to be personal data.

publish/subscribe (pub/sub)

A pattern that enables asynchronous communications among microservices to improve scalability and responsiveness. For example, in a microservices-based MES, a microservice can publish event messages to a channel that other microservices can subscribe to. The system can add new microservices without changing the publishing service.

Q

query plan

A series of steps, like instructions, that are used to access the data in a SQL relational database system.

query plan regression

When a database service optimizer chooses a less optimal plan than it did before a given change to the database environment. This can be caused by changes to statistics, constraints, environment settings, query parameter bindings, and updates to the database engine.

R

RACI matrix

See responsible, accountable, consulted, informed (RACI).

RAG

See Retrieval Augmented Generation.

ransomware

A malicious software that is designed to block access to a computer system or data until a payment is made.

RASCI matrix

See responsible, accountable, consulted, informed (RACI).

RCAC

See row and column access control.

read replica

A copy of a database that's used for read-only purposes. You can route queries to the read replica to reduce the load on your primary database.

re-architect

See 7 Rs.

recovery point objective (RPO)

The maximum acceptable amount of time since the last data recovery point. This determines what is considered an acceptable loss of data between the last recovery point and the interruption of service.

recovery time objective (RTO)

The maximum acceptable delay between the interruption of service and restoration of service.

refactor

See 7 Rs.

Region

A collection of AWS resources in a geographic area. Each AWS Region is isolated and independent of the others to provide fault tolerance, stability, and resilience. For more information, see Specify which AWS Regions your account can use.

regression

An ML technique that predicts a numeric value. For example, to solve the problem of "What price will this house sell for?" an ML model could use a linear regression model to predict a house's sale price based on known facts about the house (for example, the square footage).

rehost

See 7 Rs.

release

In a deployment process, the act of promoting changes to a production environment.

relocate

See 7 Rs.

replatform

See 7 Rs.

repurchase

See 7 Rs.

resiliency

An application's ability to resist or recover from disruptions. High availability and disaster recovery are common considerations when planning for resiliency in the AWS Cloud. For more information, see AWS Cloud Resilience.

resource-based policy

A policy attached to a resource, such as an Amazon S3 bucket, an endpoint, or an encryption key. This type of policy specifies which principals are allowed access, supported actions, and any other conditions that must be met.

responsible, accountable, consulted, informed (RACI) matrix

A matrix that defines the roles and responsibilities for all parties involved in migration activities and cloud operations. The matrix name is derived from the responsibility types defined in the matrix: responsible (R), accountable (A), consulted (C), and informed (I). The support (S) type is optional. If you include support, the matrix is called a *RASCI matrix*, and if you exclude it, it's called a *RACI matrix*.

responsive control

A security control that is designed to drive remediation of adverse events or deviations from your security baseline. For more information, see Responsive controls in *Implementing security controls on AWS*.

retain

See 7 Rs.

retire

See 7 Rs.

Retrieval Augmented Generation (RAG)

A generative AI technology in which an LLM references an authoritative data source that is outside of its training data sources before generating a response. For example, a RAG model might perform a semantic search of an organization's knowledge base or custom data. For more information, see What is RAG.

rotation

The process of periodically updating a secret to make it more difficult for an attacker to access the credentials.

row and column access control (RCAC)

The use of basic, flexible SQL expressions that have defined access rules. RCAC consists of row permissions and column masks.

RPO

See recovery point objective.

RTO

See recovery time objective.

runbook

A set of manual or automated procedures required to perform a specific task. These are typically built to streamline repetitive operations or procedures with high error rates.

S

SAML 2.0

An open standard that many identity providers (IdPs) use. This feature enables federated single sign-on (SSO), so users can log into the AWS Management Console or call the AWS API operations without you having to create user in IAM for everyone in your organization. For more information about SAML 2.0-based federation, see About SAML 2.0-based federation in the IAM documentation.

SCADA

See supervisory control and data acquisition.

SCP

See service control policy.

secret

In AWS Secrets Manager, confidential or restricted information, such as a password or user credentials, that you store in encrypted form. It consists of the secret value and its metadata.

The secret value can be binary, a single string, or multiple strings. For more information, see What's in a Secrets Manager secret? in the Secrets Manager documentation.

security by design

A system engineering approach that takes security into account through the whole development process.

security control

A technical or administrative guardrail that prevents, detects, or reduces the ability of a threat actor to exploit a security vulnerability. There are four primary types of security controls: preventative, detective, responsive, and proactive.

security hardening

The process of reducing the attack surface to make it more resistant to attacks. This can include actions such as removing resources that are no longer needed, implementing the security best practice of granting least privilege, or deactivating unnecessary features in configuration files.

security information and event management (SIEM) system

Tools and services that combine security information management (SIM) and security event management (SEM) systems. A SIEM system collects, monitors, and analyzes data from servers, networks, devices, and other sources to detect threats and security breaches, and to generate alerts.

security response automation

A predefined and programmed action that is designed to automatically respond to or remediate a security event. These automations serve as detective or responsive security controls that help you implement AWS security best practices. Examples of automated response actions include modifying a VPC security group, patching an Amazon EC2 instance, or rotating credentials.

server-side encryption

Encryption of data at its destination, by the AWS service that receives it.

service control policy (SCP)

A policy that provides centralized control over permissions for all accounts in an organization in AWS Organizations. SCPs define guardrails or set limits on actions that an administrator can delegate to users or roles. You can use SCPs as allow lists or deny lists, to specify which services or actions are permitted or prohibited. For more information, see Service control policies in the AWS Organizations documentation.

service endpoint

The URL of the entry point for an AWS service. You can use the endpoint to connect programmatically to the target service. For more information, see AWS service endpoints in *AWS General Reference*.

service-level agreement (SLA)

An agreement that clarifies what an IT team promises to deliver to their customers, such as service uptime and performance.

service-level indicator (SLI)

A measurement of a performance aspect of a service, such as its error rate, availability, or throughput.

service-level objective (SLO)

A target metric that represents the health of a service, as measured by a service-level indicator.

shared responsibility model

A model describing the responsibility you share with AWS for cloud security and compliance. AWS is responsible for security *of* the cloud, whereas you are responsible for security *in* the cloud. For more information, see Shared responsibility model.

SIEM

See security information and event management system.

single point of failure (SPOF)

A failure in a single, critical component of an application that can disrupt the system.

SLA

See service-level agreement.

SLI

See service-level indicator.

SLO

See service-level objective.

split-and-seed model

A pattern for scaling and accelerating modernization projects. As new features and product releases are defined, the core team splits up to create new product teams. This helps scale your organization's capabilities and services, improves developer productivity, and supports rapid innovation. For more information, see Phased approach to modernizing applications in the AWS Cloud.

SPOF

See single point of failure.

star schema

A database organizational structure that uses one large fact table to store transactional or measured data and uses one or more smaller dimensional tables to store data attributes. This structure is designed for use in a data warehouse or for business intelligence purposes.

strangler fig pattern

An approach to modernizing monolithic systems by incrementally rewriting and replacing system functionality until the legacy system can be decommissioned. This pattern uses the analogy of a fig vine that grows into an established tree and eventually overcomes and replaces its host. The pattern was introduced by Martin Fowler as a way to manage risk when rewriting monolithic systems. For an example of how to apply this pattern, see Modernizing legacy Microsoft ASP.NET (ASMX) web services incrementally by using containers and Amazon API Gateway.

subnet

A range of IP addresses in your VPC. A subnet must reside in a single Availability Zone.

supervisory control and data acquisition (SCADA)

In manufacturing, a system that uses hardware and software to monitor physical assets and production operations.

symmetric encryption

An encryption algorithm that uses the same key to encrypt and decrypt the data.

synthetic testing

Testing a system in a way that simulates user interactions to detect potential issues or to monitor performance. You can use Amazon CloudWatch Synthetics to create these tests.

system prompt

A technique for providing context, instructions, or guidelines to an LLM to direct its behavior. System prompts help set context and establish rules for interactions with users.

T

tags

Key-value pairs that act as metadata for organizing your AWS resources. Tags can help you manage, identify, organize, search for, and filter resources. For more information, see Tagging your AWS resources.

target variable

The value that you are trying to predict in supervised ML. This is also referred to as an *outcome variable*. For example, in a manufacturing setting the target variable could be a product defect.

task list

A tool that is used to track progress through a runbook. A task list contains an overview of the runbook and a list of general tasks to be completed. For each general task, it includes the estimated amount of time required, the owner, and the progress.

test environment

See environment.

training

To provide data for your ML model to learn from. The training data must contain the correct answer. The learning algorithm finds patterns in the training data that map the input data attributes to the target (the answer that you want to predict). It outputs an ML model that captures these patterns. You can then use the ML model to make predictions on new data for which you don't know the target.

transit gateway

A network transit hub that you can use to interconnect your VPCs and on-premises networks. For more information, see What is a transit gateway in the AWS Transit Gateway documentation.

trunk-based workflow

An approach in which developers build and test features locally in a feature branch and then merge those changes into the main branch. The main branch is then built to the development, preproduction, and production environments, sequentially.

trusted access

Granting permissions to a service that you specify to perform tasks in your organization in AWS Organizations and in its accounts on your behalf. The trusted service creates a service-linked role in each account, when that role is needed, to perform management tasks for you. For more information, see Using AWS Organizations with other AWS services in the AWS Organizations documentation.

tuning

To change aspects of your training process to improve the ML model's accuracy. For example, you can train the ML model by generating a labeling set, adding labels, and then repeating these steps several times under different settings to optimize the model.

two-pizza team

A small DevOps team that you can feed with two pizzas. A two-pizza team size ensures the best possible opportunity for collaboration in software development.

U

uncertainty

A concept that refers to imprecise, incomplete, or unknown information that can undermine the reliability of predictive ML models. There are two types of uncertainty: *Epistemic uncertainty* is caused by limited, incomplete data, whereas *aleatoric uncertainty* is caused by the noise and randomness inherent in the data. For more information, see the Quantifying uncertainty in deep learning systems guide.

undifferentiated tasks

Also known as *heavy lifting*, work that is necessary to create and operate an application but that doesn’t provide direct value to the end user or provide competitive advantage. Examples of undifferentiated tasks include procurement, maintenance, and capacity planning.

upper environments

See environment.

V

vacuuming

A database maintenance operation that involves cleaning up after incremental updates to reclaim storage and improve performance.

version control

Processes and tools that track changes, such as changes to source code in a repository.

VPC peering

A connection between two VPCs that allows you to route traffic by using private IP addresses. For more information, see What is VPC peering in the Amazon VPC documentation.

vulnerability

A software or hardware flaw that compromises the security of the system.

W

warm cache

A buffer cache that contains current, relevant data that is frequently accessed. The database instance can read from the buffer cache, which is faster than reading from the main memory or disk.

warm data

Data that is infrequently accessed. When querying this kind of data, moderately slow queries are typically acceptable.

window function

A SQL function that performs a calculation on a group of rows that relate in some way to the current record. Window functions are useful for processing tasks, such as calculating a moving average or accessing the value of rows based on the relative position of the current row.

workload

A collection of resources and code that delivers business value, such as a customer-facing application or backend process.

workstream

Functional groups in a migration project that are responsible for a specific set of tasks. Each workstream is independent but supports the other workstreams in the project. For example, the portfolio workstream is responsible for prioritizing applications, wave planning, and collecting migration metadata. The portfolio workstream delivers these assets to the migration workstream, which then migrates the servers and applications.

WORM

See write once, read many.

WQF

See AWS Workload Qualification Framework.

write once, read many (WORM)

A storage model that writes data a single time and prevents the data from being deleted or modified. Authorized users can read the data as many times as needed, but they cannot change it. This data storage infrastructure is considered immutable.

Z

zero-day exploit

An attack, typically malware, that takes advantage of a zero-day vulnerability.

zero-day vulnerability

An unmitigated flaw or vulnerability in a production system. Threat actors can use this type of vulnerability to attack the system. Developers frequently become aware of the vulnerability as a result of the attack.

zero-shot prompting

Providing an LLM with instructions for performing a task but no examples (*shots*) that can help guide it. The LLM must use its pre-trained knowledge to handle the task. The effectiveness of zero-shot prompting depends on the complexity of the task and the quality of the prompt. See also few-shot prompting.

zombie application

An application that has an average CPU and memory usage below 5 percent. In a migration project, it is common to retire these applications.