Data Analytics Lens

AWS Well-Architected Framework

Data Analytics Lens: AWS Well-Architected Framework

Table of Contents

Introduction

Publication date: **October 29, 2021** (*Document history* (p. 64))

This document describes the AWS Well-Architected Data Analytics Lens, a collection of customer-proven best practices for designing well-architected analytics workloads. The Data Analytics Lens contains insights that AWS has gathered from real-world case studies, and helps you learn the key design elements of well-architected analytics workloads along with recommendations for improvement. The document is intended for IT architects, developers, and team members who build and operate analytics systems.

How to use the lens

The AWS Well-Architected Framework helps you understand the pros and cons of decisions you make while building systems on AWS.

By using the framework, you learn architectural best practices for designing and operating reliable, secure, efficient, and cost-effective systems in the cloud. It provides a way for you to consistently measure your architectures against best practices and identify areas for improvement. We believe that having well-architected systems greatly increases the likelihood of business success.

In this “Lens” we focus on how to design, deploy, and architect your analytics application workloads in the AWS Cloud. For brevity, we have only covered details from the Well-Architected Framework that are specific to analytics workloads. You should still consider best practices and questions that have not been included in this document when designing your architecture. We recommend that you read the AWS Well-Architected Framework.

This document is intended for those in technology roles, such as chief technology officers (CTOs), architects, developers, and operations team members. After reading this document, you will understand AWS best practices and strategies to use when designing architectures for analytics applications and environment.

Workload context checklist

To better understand your business's context, you must gather the following information.

ID	Priority	Workload Context
☐ C1	Required	Name of the workload
☐ C2	Required	Description that contains the business purposes, key performance indicators (KPIs), and the intended users of the workload
☐ C3	Required	Review owner who leads the lens review
☐ C4	Required	Workload owner who is responsible for maintaining the workload
☐ C5	Required	Business stakeholders who sponsor the workload
☐ C6	Required	Business partners who have a stake in the workload, such as information security, finance, and legal
☐ C7	Recommended	Architecture design document that describes the workload
☐ C8	Recommended	AWS Account IDs associated with the workload
☐ C9	Recommended	Regulatory compliance requirements relevant to the workload (if any)

Well-Architected design principles

This section describes the design principles, best practices, and improvement suggestions that are relevant when designing your workload architecture. For brevity, only questions that are specific to analytics workloads are included in the Analytics Lens. We recommend you also read and apply the guidance found in each Well-Architected pillar, which includes foundational best practices for operational excellence, security, performance efficiency, reliability, and cost optimization that are relevant to all workloads.

Pillars

Operational excellence

The Operational Excellence pillar includes the ability to support development and run workloads effectively, gain insight into their operations, and to continually improve supporting processes and procedures to deliver business value.

1 - Monitor the health of the analytics pipelines

How do you measure the health of your analytics workload? Data analytics workloads often involve multiple systems and process steps working in coordination. It is imperative that you monitor not only individual components but also the interaction of dependent processes to ensure a healthy data analytics workload.

ID	Priority	Best Practice
☐ BP 1.1	Required	Validate the data quality of source systems before moving to analytics
☐ BP 1.2	Required	Monitor the planned arrival of recent data from the source systems
☐ BP 1.3	Required	Define and measure the schedules of recurring analytics jobs
☐ BP 1.4	Required	Define and measure the runtime durations of analytics jobs

For more details, refer to the following blogs:

- AWS Compute Blog: Monitoring and troubleshooting serverless data analytics applications
- AWS Big Data Blog: Building a serverless data quality and analysis framework with Deequ and AWS Glue

Best Practice 1.1 - Validate the data quality of source systems before moving to analytics

Data quality can have a drastic impact on the success or failure of data analytics output. To avoid committing significant resources to processing potentially poor-quality data, you should validate the source data quality before starting the analytics work. Dataset validation can often be done quickly on a subset or the latest data range to look for obvious data defects, such as missing values, anomalous data, or wrong data types, that would fail the analytics job completion, or lead to completion of the job with inaccurate results.

Suggestion 1.1.1 - Implement data validation mechanisms

Validation mechanisms should check for the expected number of rows, for null values, and for wrong data types before further processing an analytics dataset.

Suggestion 1.1.2 - Notify stakeholders and use business logic to determine how to remediate data that is not valid

Determine how to address data that is not valid. In some cases, it's more efficient to impute missing values, but in other cases it's more efficient to block processing until the data quality issue can be addressed.

Best Practice 1.2 - Monitor the planned arrival of recent data from the source systems

Under normal operations, data analytics workloads may produce outputs periodically to meet business deadlines. A single component of a data processing pipeline might be healthy because it is running and available for work, but if no data arrives for processing, the business deadline could be missed.

Suggestion 1.2.1 - Monitor for the arrival or availability of new data, and notify if the expected duration between data arrival is too long

When event-driven systems rely on incoming data to initiate an analytics processing job, the job will not begin if new data does not arrive. Implement systems to track the time between new data alerts, and alarm if the analytics job does not start within the expected time window.

Best Practice 1.3 - Define and measure the schedules of recurring analytics jobs

Recurring analytics jobs that run on a schedule (instead of being event-driven) will have a defined start time. Emit metrics indicating when the job should have started and notify if the job has not started within a predefined amount of time.

Suggestion 1.3.1 - Monitor the start time for recurring analytics processing jobs compared to the expected start time

When the start of the job has exceeded a defined time window past the expected start time, emit an alarm.

Best Practice 1.4 - Define and measure the runtime durations of analytics jobs

Configure data analytics jobs to emit metrics indicating when processing work has started and completed. Use these metrics to calculate runtime durations. Notify if a job has started but not completed within the expected threshold.

Suggestion 1.4.1 - Monitor the start and end times for analytics processing steps or the overall analytics job

When the time duration of a job exceeds a threshold without completion, emit an alarm.

2 - Modernize deployment of the analytics jobs and applications

How do you deploy ETL jobs and applications in a controlled and reproducible way? Using modern development practices, such as continuous integration/continuous delivery (CI/CD), can help ensure that changes are rolled out in a controlled and repeatable way. Use test automation to verify infrastructure, code, and data changes in stages to ensure the operational stability of the entire analytics pipeline.

ID	Priority	Best Practice
☐ BP 2.1	Recommended	Use version control for job and application changes
☐ BP 2.2	Recommended	Set up testing data and a staging environment
☐ BP 2.3	Recommended	Test and validate analytics jobs and application deployments
☐ BP 2.4	Recommended	Roll back failed deployments and backfill the data
☐ BP 2.5	Recommended	Build standard operating procedures for deployment, test, rollback, and backfill tasks
☐ BP 2.6	Recommended	Automate the standard operating procedures

For more details, refer to the following documentation:

- AWS Whitepaper: Modern Application Development on AWS
- AWS DevOps Blog: Deploy data lake ETL jobs using CDK Pipelines

Best Practice 2.1 - Use version control for job and application changes

Use version-controlled code repositories for both analytics infrastructure as code and analytics applications logic. Version control systems allow tracking changes and the ability to revert to previous versions of analytics systems should changes cause unintended consequences.

Suggestion 2.1.1 - Implement infrastructure as code and application logic version control systems

Use different code repositories, such as AWS CodeCommit, GitHub, or Bitbucket, for infrastructure as code and application logic.

Best Practice 2.2 - Set up testing data and a staging environment

Using a known and unchanging dataset for test purposes helps ensure that when changes are made to the analytics environment or analytics application code, tests can be compared to previous versions. Confirm that test datasets accurately represent real-world data. This allows the analytics workload developer to confirm proper outcomes from the analytics job, in addition to compare test results to

previous versions. It is very difficult to compare test job runs when the underlying dataset changes between tests. Use staging environments for tests so that you do not impact production.

Suggestion 2.2.1 - Use a curated dataset to test application logic and performance improvements, such that code changes can be comparatively analyzed for the desired outcomes

Analytics jobs under development should use the same curated, or known-good, dataset to compare results between tests of different versions of your code. Using the same dataset for all tests allows demonstrating improvement over time, as well as making it easier to recognize regressions in your code.

Suggestion 2.2.2 - Use a random sample of recent data to validate application edge cases and regressions have not been introduced

Use a statistically valid random sample of recent data to confirm that the analytics solution continues to perform under real-world conditions. Using a sample of recent data also allows you to more easily recognize if your dataset characteristics have shifted or if anomalous data has been recently introduced to your data.

Suggestion 2.2.3 - Establish separate staging environments to fully test changes before going live

Use separate environments, such as development, test, and production, to allow riskier feature development to be introduced without disrupting production systems. Test changes for accuracy and performance before a business-critical deployment.

Best Practice 2.3 - Test and validate analytics jobs and application deployments

Before making changes in production environments, use standard and repeatable automated tests to validate performance and accuracy of results.

Suggestion 2.3.1 - Automate the deployment and testing of changes to infrastructure and applications

Use services, such as AWS CodePipeline and AWS Step Functions, to programmatically test changes and validate performance results.

Best Practice 2.4 - Roll back failed deployments and backfill the data

Design your deployment methods to catch failed deployments and automatically roll back to previous versions. If necessary, track downstream data changes that might have occurred from the failed deployment and backfill the data to ensure data quality.

Suggestion 2.4.1 - Use infrastructure as code and version control systems so that a failed deployment can be rolled back to a previous good state

Follow software development best practices when building analytics systems. For example, deploy resources using code templates, such as AWS CloudFormation or Hashicorp Terraform, so that all deployments occur exactly as intended. Use version control systems (for example, code repositories such as AWS CodeCommit or GitHub) to hold current and previous versions of your code templates so that if a new change results in unwanted outcomes, you can easily roll back to the previous code template.

Best Practice 2.5 - Build standard operating procedures for deployment, test, rollback, and backfill tasks

Standard operating procedures for deployment, test, rollback, and data backfill tasks allow faster deployments, reduce the number of errors that reach production, and make remediation easier if

a deployment results in unintended consequences. The end result will be higher-quality analytics outcomes for the business.

Suggestion 2.5.1 - Document and use standard operating procedures for implementing changes in your analytics workload

Standard operating procedures will allow teams to confidently make changes, thus avoiding repeatable mistakes and reduce the chance of human error.

Best Practice 2.6 - Automate the standard operating procedures

Automating standard operating procedures for deployment, test, rollback, and data backfill tasks allow faster deployments, less chance for errors to reach production, and easier remediation if deployments result in unintended consequences. The end-result will be a faster time-to-value for the business and less frequent errors in operation.

Suggestion 2.6.1 - Use automation to perform changes to underlying analytics infrastructure or application logic

Automated tests can determine when changes have unintended consequences and can roll back without human intervention.

3 – Build financial accountability models for data and workload usage

How do you measure and attribute the analytics workload financial accountability? As your business continues to evolve, so will your analytics workload and your stakeholders' use of data analytics. Data analytics systems and the data generated from these systems will grow over time into a mix of both broadly-shared and isolated-team resources. Establish a financial attribution model for these resources. Teams will then understand how their use of data analytics influences costs to the business and this promotes a culture of accountability and frugality.

ID	Priority	Best Practice
☐ BP 3.1	Recommended	Measure and notify of the data storage and processing costs per user of the workload
☐ BP 3.2	Recommended	Allow downstream systems to use their own resources for analytics jobs (bring your own infrastructure)
☐ BP 3.3	Recommended	Build a common, shared processing system and measure the cost per analytics job (bring your own query)
☐ BP 3.4	Recommended	Build an internal billback model for analytics workload usage
☐ BP 3.5	Recommended	Restrict and record resource allocation permissions using AWS Identity and Access Management (IAM)

For more details, refer to the following:

- AWS Cloud Financial Management Blog: Cost Allocation Blog Series #1: Cost Allocation Basics That You Need to Know
- AWS Cloud Enterprise Strategy Blog: Who Pays? Decomplexifying Technology Charges
- AWS Cloud Enterprise Strategy Blog: Strategy for Efficient Cloud Cost Management

- AWS Cloud Financial Management Blog: Trends Dashboard with AWS Cost and Usage Reports, Amazon Athena and Amazon QuickSight
- AWS Well-Architected Labs: Cost Optimization

Best Practice 3.1 - Measure and notify of the data storage and processing costs per user of the workload

Data analytics systems have both recurring stable costs and per-use costs, for example, a weekly reporting job with relatively static data storage fees in addition to the periodic transient computation's runtime duration fee. Establish a financial attribution mechanism so that when analytics systems are run, data storage and usage data is captured such that a user (business unit, team, or individual) can be notified of their consumption at regular intervals.

Suggestion 3.1.1 - Use tagging or other attribution methods to identify data storage ownership

Aggregate costs by owner and update your financial tools with storage costs.

Best Practice 3.2 - Allow downstream systems to use their own resources for analytics jobs (bring your own infrastructure)

In some cases, teams will establish their own data analytics resources that depend on data feeds from upstream systems. Determine when teams will benefit from building their own infrastructure, balancing required agility, team skillset, and provisioning the right resources for the job. In this case, individual teams will be responsible for the costs associated with the resources they control.

Suggestion 3.2.1 - Perform regular reviews of analytics operations to determine if the business will benefit from teams managing their own infrastructure

In some cases, teams will want to maintain and manage their own infrastructure. Individual team ownership allows greater flexibility and agility when making system design choices with fewer dependencies on other users. Furthermore, individual team ownership provides clear cost visibility to the team that owns it.

Suggestion 3.2.2 - Use infrastructure as code and governance tools, such as AWS Service Catalog, to allow teams to self-provision infrastructure within approved constraints

When teams can deploy their own infrastructure, often businesses want to apply governance and guardrails to maintain adherence to corporate policies. AWS Service Catalog allows teams to deploy sets of resources with a defined selection of parameters, thus ensuring only the resource types allowed by the governance team can be deployed.

Best Practice 3.3 - Build a common, shared processing system and measure the cost per analytics job (bring your own query)

In some cases, it will be more efficient to have a shared processing system where individual teams can send requests for data analytics. In this case, measure the number of requests for processing by individual teams, and the datasets generated by those requests, so that each teams' consumption can be attributed for the shared resource.

Suggestion 3.3.1 - Perform regular reviews of analytics operations to determine if the business will benefit from shared, centralized analytics infrastructure

In some cases, a centralized team will maintain and manage infrastructure for the benefit of multiple groups to share. Shared infrastructure allows greater utilization of the resources deployed and concentrated skillsets for infrastructure management.

Suggestion 3.3.2 - Implement a per-request tracking mechanism which allows utilization attribution to the different teams

With a shared resource, some businesses still want to maintain cost visibility to the teams using those resources. Implementing a per-request tracking mechanism will allow measuring the associated resource billing metrics during the job and attribute those portions to the requester. Those metrics and the associated users will be aggregated into a cost visibility report.

Best Practice 3.4 - Build an internal billback model for analytics workload usage

After establishing the best practices of measuring and attributing teams' use of individual and shared resources, build an internal billback model to give those teams' financial responsibility for their use of data analytics.

Suggestion 3.4.1 - Implement a cost-visibility and internal billback method to aggregate the team's utilization of analytics resources

Notify teams of their analytics usage costs periodically, or build dashboards that allow teams to gain visibility into how their work impacts costs to the business in a self-service way.

Best Practice 3.5 - Restrict and record resource allocation permissions using AWS Identity and Access Management (IAM)

Create specific IAM roles to provide authorization to provision expensive resources. Remove authorization for individuals to provision those resources. Use the record of the identities assuming those roles to provision expensive resources as part of your cost attribution model.

Suggestion 3.5.1 - Create a cost governance framework that uses specialized IAM roles, rather than individual IAM users, to provision costly infrastructure

Restrict the authorization to launch costly resources to specific IAM roles created for that purpose. When a user assumes that role, log the actions and the user who has assumed that role.

Suggestion 3.5.2 - Use IAM logs to attribute users assuming these specialized IAM roles for cost attribution

As part of your cost-allocation governance, automatically process the IAM logs so that cost allocation is properly attributed.

Security

The security pillar encompasses the ability to protect data, systems, and assets to take advantage of cloud technologies to improve your security.

4 - Classify and protect data

How do you classify and protect data in analytics workload? Because analytics workloads ingest data from source systems, the owner of the source data should define the data classifications. As the analytics workload owner, you should honor the source data classifications and implement the corresponding data protection policies of your organization. Share the data classifications with the downstream data consumers to permit them to honor the data classifications in their organizations and policies as well.

Data classification helps to categorize organizational data based on sensitivity and criticality, which then helps determine appropriate protection and retention controls on that data.

ID	Priority	Best Practice
☐ BP 4.1	Required	Understand data classifications and their protection policies
☐ BP 4.2	Required	Identify the source data owners and have them set the data classifications
☐ BP 4.3	Required	Record data classifications into the Data Catalog so that analytics workload can understand
☐ BP 4.4	Required	Implement encryption policies for each class of data in the analytics workload
☐ BP 4.5	Required	Implement retention and backup policies for each class of data in the analytics workload
☐ BP 4.6	Recommended	Require downstream systems honor the data classifications

For more details, refer to the following information:

- AWS Database Blog: Best practices for securing sensitive data in AWS data stores
- AWS Security Blog: Discover sensitive data by using custom data identifiers with Amazon Macie
- Amazon Macie User Guide: What is Amazon Macie?
- AWS Key Management Service Developer Guide: What is AWS Key Management Service?
- AWS Whitepaper: Data Classification: Secure Cloud Adoption

Best Practice 4.1 - Understand data classifications and their protection policies

Data classification in your organization is key to determining how data must be protected while at rest and in transit. For example, since an analytics workload needs to copy and share data between operations and systems, we recommend that you encrypt the data while it's in motion. Such a data protection strategy helps to prevent data loss, theft, and corruption, and helps minimize the impact caused by malicious activities or unintended access.

Suggestion 4.1.1 - Identify classification levels

Use the Data Classification whitepaper to help you identify different classification levels. Four commons levels used are Restricted, Confidential, Internal, and Public. These levels can vary based on the industry and compliance requirements of your organization.

Suggestion 4.1.2 - Define access rules

Let the data owners define the data access rules, based on the sensitivity and criticality of the data. Refer to the following blogs for more information:

- AWS Security Blog: How to scale your authorization needs by using attribute-based access control with S3
- AWS Big Data Blog: Control data access and permissions with AWS Lake Formation and Amazon EMR
- AWS Big Data Blog: Enforce column-level authorization with Amazon QuickSight and AWS Lake Formation

Suggestion 4.1.3 - Identify security zone models to isolate data based on classification

Design the security zone models from AWS account levels down to AWS resource levels. For example, consider building AWS multi-account models to isolate different classes of data from AWS account level. Or, you can consider separating out dev/test resources from production ones from AWS account level or from resource levels. Refer to the following whitepapers for more information:

- AWS Whitepaper: An Overview of the AWS Cloud Adoption Framework
- AWS Whitepaper: Organizing Your AWS Environment Using Multiple Accounts
- AWS Whitepaper: Security Pillar - AWS Well-Architected Framework

Suggestion 4.1.4 - Identify sensitive information and define protection policies

Discover sensitive data by using custom data identifiers in Amazon Macie. Based on the sensitivity and criticality of the data, implement data protection policies to prevent unauthorized access. Due to compliance requirements, data might be masked or deleted after processing in some cases. We recommend that you apply data protection policies to data both at rest and in transit.

Best Practice 4.2 - Identify the source data owners and have them set the data classifications

Identify the owners of the source data, such as data lake administrators, business data owners, or IT storage administrators, and confirm what level of protection is required for the data within the analytics workload. Data classifications follow the data as it moves throughout the analytics workflow to ensure that the data is protected, and to determine who or which systems are allowed to access the data. By following the organization's classification policies, the analytics workload should be able to differentiate the data protection implementations for each class of data. Because each organization has different kinds of classification, the analytics workload should provide a strong logical boundary between processing data of different sensitivity levels.

Suggestion 4.2.1 - Assign owners per each dataset

A dataset, or a table in relational database technology, is a collection of data. A Data Catalog is a collection of metadata that helps centralize share, search, and manage permissions. The administrator of the analytics workload should know who are the owners for each dataset, and should assign the dataset ownership into the Data Catalog.

Suggestion 4.2.2 - Define attestation scope and reviewer as additional scope for sensitive data

As the owner of the analytics workload, you should know the data owner for each dataset. For example, when a dataset has permission issues in the organization while it's classified as highly sensitive, you may need to talk to the dataset owner and have him or her resolve the issues.

Suggestion 4.2.3 - Set expiry for data ownership and attestation, and have owners reconfirm periodically

As businesses change, the data owners and the data classifications might change as well. Run campaigns periodically, such as quarterly or yearly, to request each of the dataset owners to reconfirm that they are still the right owners, and that the data classifications are still accurate.

Best Practice 4.3 - Record data classifications into the Data Catalog so that analytics workloads can understand

Allow processes to update the Data Catalog so it can provide a reliable record of where the data is located and its precise classification. To effectively protect the data, analytics systems should know the

classifications of the source data so that the systems can govern the data according to business needs. For example, if the business requires that confidential data be encrypted using team-owned private keys, such as from AWS Key Management Service (AWS KMS), the analytics workload should be able to determine which data is classified as confidential by referencing its Data Catalog.

Suggestion 4.3.1 - Use tags to indicate the data classifications

Use tags to designate the classification of sensitive data in data stores. Tags allow discoverability of data sensitivity without directly exposing the underlying data. They also can be used to authorize access in attribute-based access control (ABAC) schemes.

- AWS Lake Formation Developer Guide: What Is AWS Lake Formation?

Suggestion 4.3.2 - Record lineage of data to track changes in the Data Catalog

Data lineage is a relation among data and the processing systems. For example, the data lineage tells where the source system of the data is, what data derived from it, and which downstream systems are reading it. You should be able to discover, record, and visualize the data lineage from source to downstream systems. For example, you can use Apache Atlas on Amazon EMR to classify, track lineage, and discover metadata.

- AWS Big Data Blog: Metadata classification, lineage, and discovery using Apache Atlas on Amazon EMR

Best Practice 4.4 - Implement encryption policies for each class of data in the analytics workload

Ensure that the analytics workload encrypts the data in accordance with the classification policies. For example, if the business's classification policy allows systems to encrypt public data using AWS managed keys, the analytics systems should encrypt data in Amazon S3 using S3 server-side encryption. However, if the classification policy requires you to manage the encryption private keys as well as data, you should consider using customer managed keys in AWS Key Management Service (AWS KMS) to manage your own cryptographic keys for the storage encryption.

Suggestion 4.4.1 - Implement encryption policies for data at rest and in transit

Each analytics solution provides the encryption methods by its own way. Review the viable encryption methods of your solutions, and implement the encryptions. Refer to the encryption implementation guides, such as the following:

- AWS Key Management Service Best Practices Whitepaper: AWS-managed and Customer-managed CMKs
- AWS Big Data Blog: Best Practices for Securing Amazon EMR
- AWS Big Data Blog: Encrypt Your Amazon Redshift Loads with Amazon S3 and AWS KMS
- AWS Big Data Blog: Encrypt and Decrypt Amazon Kinesis Records Using AWS KMS
- AWS Partner Network (APM) Blog: Data Tokenization with Amazon Redshift and Protegrity

Best Practice 4.5 - Implement data retention policies for each class of data in the analytics workload

The business's data classification policies determine how long the analytics workload should retain the data and how long backups should be kept. These policies help ensure that every system follows the data security rules and compliance requirements. The analytics workload should implement data retention and backup policies according to these data classification policies. For example, if the

policy requires every system to retain the operational data for five years, the analytics systems should implement rules to keep the in-scoped data for five years.

Suggestion 4.5.1 - Create backup requirements and policies based on data classifications

Data backup should be based on business requirements on tolerance in time related to data loss, such as recovery point objective (RPO), recovery time objective (RTO), data classifications, and the compliance and audit requirements for specific datasets.

Suggestion 4.5.2 - Create data retention requirement policies based on the data classifications

Avoid creating blanket retention policies. Instead, policies should be tailored to individual data assets based on the retention requirements. Refer to the following implementation guides:

- AWS Big Data Blog: Building a cost efficient, petabyte-scale lake house with Amazon S3 lifecycle rules and Amazon Redshift Spectrum: Part 1
- AWS Big Data Blog: Retaining data streams up to one year with Amazon Kinesis Data Streams
- AWS Big Data Blog: Retain more for less with UltraWarm for Amazon OpenSearch Service

Best Practice 4.6 - Require downstream systems to honor the data classifications

Since other data-consuming systems will access the data that the analytics workload shares, the workload should require the downstream systems to implement the required data classification policies. For example, if the analytics workload shares the data that is required to encrypt using customer-managed private keys in AWS Key Management Service (KMS), the downstream systems should also acknowledge and implement such a data protection policy themselves. This helps to ensure that the data is protected throughout the data pipelines.

Suggestion 4.6.1 - Have a centralized, shareable catalog with cross-account access to ensure that data owners manage permissions for downstream systems

Downstream systems can run on their own AWS accounts other than the one of analytics workload. Meanwhile, the downstream systems should be able to discover the data, acknowledge the required data protection policies, and to access the data. To allow the downstream systems use the data from analytics workload, the analytics workload should provide cross-account access for each dataset. Refer to the following blogs:

- AWS Big Data Blog: Cross-account AWS Glue Data Catalog access with Amazon Athena
- AWS Big Data Blog: How JPMorgan Chase built a data mesh architecture to drive significant value to enhance their enterprise data platform

Suggestion 4.6.2 – Monitor the downstream systems' eligibility to access classified data from the analytics workload

Monitor the downstream systems' eligibility to handle sensitive data. For example, you do not want development or test Amazon Redshift clusters to read sensitive data from the analytics workload. If your organization runs a program that certifies what systems are eligible to process which classes of data, periodically verify that each downstream system's data processing eligibility levels and the list of data that it accesses is appropriate.

5 - Control the data access

How do you manage access to data within source, analytics, and downstream systems? An analytics workload is a centralized repository of data from source systems, and distributes the data to downstream

systems. The upstream and downstream systems, therefore, might be owned by different teams. As the analytics workload owner, you should honor the source systems' access management policies when connecting to the source systems, secure the access of the data in the analytics workload, and securely share the data to downstream systems without violating the data classification policies of the source systems.

ID	Priority	Best Practice
☐ BP 5.1	Required	Allow data owners to determine who or which systems can access data in analytics and downstream workloads
☐ BP 5.2	Required	Build user identity solutions that uniquely identify people and systems
☐ BP 5.3	Required	Implement the required data authorization models
☐ BP 5.4	Recommended	Establish an emergency access process to the source, analytics, and downstream systems

For more details, refer to the following documentation:

- AWS Lake Formation Developer Guide: Lake Formation Access Control Overview
- Amazon Athena User Guide: Identity and Access Management in Athena
- Amazon Athena User Guide: Enabling Federated Access to the Athena API
- Amazon Redshift Database Developer Guide: Managing database security
- Amazon EMR Management Guide: AWS Identity and Access Management for Amazon EMR
- Amazon EMR Management Guide: Use Kerberos authentication
- Amazon EMR Management Guide: Use an Amazon EC2 key pair for SSH credentials

Best Practice 5.1 - Allow data owners to determine which people or systems can access data in analytics and downstream workloads

Data owners are the people that have direct responsibility for data protection. For instance, the data owners want to determine which data is publicly accessible, or which data is restricted access to whom or what systems. The data owners should be able to provide data access rules, so that the analytics workload can implement the rules.

Suggestion 5.1.1 – Identify data owners and assign roles

Data stewardship is the management and oversight of an organization's data assets to help provide business users with high-quality data that is easily accessible in a consistent manner. Because the analytics workload consolidates multiple datasets into a central place, each dataset is owned by different teams or people. So, it is important for the analytics workload to identify which dataset is owned by whom to have the owners control the data access permissions.

Suggestion 5.1.2 – Identify permission using permission matrix for users and roles based on actions performed on the data by users and downstream systems

To aid in identifying and communicating data-access permissions, an Access Control Matrix is a helpful method to document which users, roles, or systems have access to which datasets and describe what actions they can perform. Below is a sample matrix for two users, two roles for two schemas with a table in them:

Permissions	Read	Write
Schema 1	User1, User2, Role1, Role2	Role1
Schema 1 / Table 1	User1, User2, Role1, Role2	Role2
Schema 2	User1, User2, Role1, Role2	User1, Role1
Schema 2 / Table 2v	User1, User2, Role1, Role2	User2, Role2

The matrix format can help identify the least permission needed to various resources and avoid overlaps. An Access Control Matrix should be thought of as an abstract model of permissions at a given point in time. Periodically review the actual access permissions against the permission matrix document to ensure accuracy.

Best Practice 5.2 - Build user identity solutions that uniquely identify people and systems

To effectively control data access, the analytics workload should be able to uniquely identify the people or systems. For example, the workload should be able to tell who accessed to the data by looking at the user identifiers, such as user names, tags, or IAM role names with confidence that the identifier represents only one people or system.

For more details, refer to the following documentation:

- AWS Big Data Blog: Amazon Redshift identity federation with multi-factor authentication
- AWS Big Data Blog: Federating single sign-on access to your Amazon Redshift cluster with PingIdentity
- AWS Database Blog: Get started with Amazon Elasticsearch Service: Use Amazon Cognito for Kibana access control
- AWS Partner Network (APN) Blog: Implementing SAML AuthN for Amazon EMR Using Okta and Column-Level AuthZ with AWS Lake Formation
- AWS CloudTrail User Guide: How AWS CloudTrail works with IAM

Suggestion 5.2.1 - Centralize workforce identities

It's a best practice to centralize your workforce identities, which allows you to federate with AWS Identity and Access Management (IAM) using AWS IAM Identity Center (successor to AWS Single Sign-On) (IAM Identity Center) or another federation provider. In Amazon Redshift, IAM roles can be mapped to Amazon Redshift database groups. In Amazon EMR, IAM roles can be mapped to an Amazon EMR security configuration or an Apache Ranger Microsoft Active Directory group-based policy. In AWS Glue, IAM roles can be mapped to AWS Glue Data Catalog resource policies.

AWS analytics services – such as Amazon OpenSearch Service and Amazon DynamoDB – allow integration with Amazon Cognito for authentication. Amazon Cognito lets you add user sign-up, sign-in, and access control to your web and mobile apps. Amazon Cognito scales to millions of users and supports sign-in with social identity providers, such as Apple, Facebook, Google, and Amazon, and enterprise identity providers via SAML 2.0 and OpenID Connect.

For more details, refer to the following documentation:

- AWS Big Data Blog: Federate Database User Authentication Easily with IAM and Amazon Redshift
- WS Big Data Blog: Federating single sign-on access to your Amazon Redshift cluster with PingIdentity
- Amazon EMR Management Guide: Allow AWS IAM Identity Center (successor to AWS Single Sign-On) for Amazon EMR Studio

Best Practice 5.3 - Implement the required data access authorization models

User authorization determines what actions a user is permitted to take on the data or resource. The data owners should be able to use the authorization methods to protect their data as needed. For example, if the data owners need to control which users are allowed to view certain columns of data, the analytics workload should provide column-wise data access authorization along with user group management for an effective control.

Suggestion 5.3.1 - Implement IAM policy-based data access controls

Limit access to sensitive data stores with IAM policies where possible. Provide systems and people with rotating short-term credentials via role-based access control (RBAC).

For more details, refer to the following blog:

- AWS Big Data Blog: Restrict access to your AWS Glue Data Catalog with resource-level IAM permissions and resource-based policies

Suggestion 5.3.2 - Implement dataset-level data access controls

As dataset owners require independent rules of granting data access, you should build the analytics workloads to have the dataset owners control the data access per each dataset level. For example, if the analytics workload hosts a shared Amazon Redshift cluster, the owners of the individual table should be able to authorize the table read and write independently.

For more details, refer to the following blog:

- AWS Big Data Blog: Validate, evolve, and control schemas in Amazon MSK and Amazon Kinesis Data Streams with AWS Glue Schema Registry

Suggestion 5.3.3 - Implement column-level data access controls

Care should be taken that end users of analytics applications are not exposed to sensitive data. Downstream consumers of data should only access the limited view of data necessary for that analytics purpose. Enforce that sensitive data is not exposed using column-level restrictions, for example, mask the sensitive columns to downstream systems so an accidental exposure is avoided.

For more details, refer to the following blog:

- AWS Big Data Blog: Allow fine-grained permissions for Amazon QuickSight authors in AWS Lake Formation
- AWS Partner Network (APN) Blog: Implementing SAML AuthN for Amazon EMR Using Okta and Column-Level AuthZ with AWS Lake Formation
- AWS Big Data Blog: Implementing Authorization and Auditing using Apache Ranger on Amazon EMR

Best Practice 5.4 - Establish an emergency access process to the source, analytics, and downstream systems

Emergency access allows expedited access to your workload in the unlikely event of an automated process or pipeline issue. This will help you rely on least privilege access, but still provide users the right level of access when they require it.

Suggestion 5.4.1 - Ensure that risk analysis is done on your analytics workload by identifying emergency situations and a procedure to allow emergency access

Identify the potential events that can happen from source systems, analytics workload, and downstream systems. Quantify the risk of each event such as likelihood (low / medium / high) and the size of business impact (small / medium / large). For example:

- Source system unavailability event would be rare, but it will impact every downstream system.
- Downstream system unavailability event might be often, but the business impact will be limited to the particular downstream system owner.

Once you identified priority risks, discuss with the source and downstream system owners on how to allow analytics workload access to the source and downstream systems to continue the data processing business.

6 – Control the access to workload infrastructure

How do you protect the infrastructure of the analytics workload? Analytics environments change based on the evolving requirements of data processing and distribution. Ensure that the environment is accessible with the least permissions necessary. Automate auditing of environment changes and alert in case of abnormal environment access.

ID	Priority	Best Practice
☐ BP 6.1	Required	Prevent unintended access to the infrastructure
☐ BP 6.2	Required	Implement least permissions policy for source and downstream systems
☐ BP 6.3	Required	Monitor the infrastructure changes and the user activities against the infrastructure
☐ BP 6.4	Required	Secure the audit logs that record every data or resource access in analytics infrastructure

Best Practice 6.1 - Prevent unintended access to the infrastructure

Grant least privilege access to infrastructure to help prevent inadvertent or unintended access to the infrastructure. For example, you might want to make sure that anonymous users are not allowed to access to the systems, and that the systems are deployed into isolated network spaces. Network boundaries isolate analytics resources and restrict network access. Network access control lists (NACLs) act as a firewall for controlling traffic in and out. Define the network boundaries of the analytics systems and only allow intended access, to reduce the risk of inadvertent access.

Suggestion 6.1.1 – Ensure that resources in the infrastructure have boundaries

Use infrastructure boundaries for services, such as databases. Place services in their own VPC private subnets that are configured to allow connections only to needed analytics systems.

Use AWS Identity and Access Management (IAM) Access Analyzer for all AWS accounts that are centrally managed through AWS Organizations . This allows security teams and administrators to uncover unintended access to resources from outside their AWS organization within minutes. You can proactively

address whether any resource policies across any of your accounts violate your security and governance practices by allowing unintended access.

Best Practice 6.2 - Implement least privilege policies for source and downstream systems

The principle of least privilege works by giving only enough access for systems to do the job. Set an expiry on temporary permissions to ensure that re-authentication occurs periodically. The system actions on the data should determine the permission and granting permissions to other systems should not be permitted.

Suggestion 6.2.1 - Ensure permissions are least for the action performed by user/system

Identify the minimum privileges that each user/system requires, and only allow the permissions that they need. For example, if a downstream system needs to read an Amazon Redshift table from analytics workload, only give the read permission for the table using Amazon Redshift user privilege controls.

For more details, refer to the following documentation:

- AWS Security Blog: Techniques for writing least privilege IAM policies
- Amazon Redshift Database Developer Guide: Managing database security
- AWS Security Blog: IAM Access Analyzer makes it easier to implement least privilege permissions by generating IAM policies based on access activity

Suggestion 6.2.2 - Implement the two-person rule to prevent accidental or malicious actions

Even if you implemented the least privilege policies, someone needs to have critical permissions for the business such as deleting datasets from analytics workloads.

The two-person rule is a safety mechanism that requires the presence of two authorized personnel to perform tasks that are considered important. It has its origins in military protocol, but the IT security space has also widely adopted the practice.

By implementing the two-person rule, you can have additional prevention of accidental or malicious actions of the people who have critical permissions.

Best Practice 6.3 - Monitor the infrastructure changes and the user activities against the infrastructure

As the infrastructure changes over time, you should monitor what has been changed by whom. It is to ensure such changes are deliberate and the infrastructure is still protected.

Suggestion 6.3.1 – Monitor the infrastructure changes

You want to know every infrastructure change and want to know that such changes are deliberate. Monitor the infrastructure changes using available methods on your team. For example, you can implement an operation procedure to review the infrastructure configurations every quarter of the year. Or, you can use AWS services which assist you to monitor the infrastructure changes with less effort.

For more details, refer to the following documentation:

- AWS Config Developer Guide: What Is AWS Config?
- Amazon Inspector User Guide: What is Amazon Inspector?
- Amazon GuardDuty User Guide: Amazon S3 protection in Amazon GuardDuty

Suggestion 6.3.2 - Monitor the user activities against the infrastructure

You want to know who change the infrastructure when, so that you can see if any given infrastructure change is performed by an authorized person or system. To do so, as examples, you can implement an operation procedure to review the AWS CloudTrail audit logs every quarter of the year. Or you can implement near-real time trend analysis using AWS services such as Amazon CloudWatch Logs Insights.

For more details, refer to the following documentation:

- AWS CloudTrail User Guide: Monitoring CloudTrail Log Files with Amazon CloudWatch Logs
- AWS Management & Governance Blog: Analyzing AWS CloudTrail in Amazon CloudWatch

Best Practice 6.4 - Secure the audit logs that record every data or resource access in analytics infrastructure

Audit logs are records that record events as they happened and should be immutable. These logs provide proof of actions and help in identifying misuse. The logs provide a baseline for analysis or for an audit when initiating an investigation. By using a fault-tolerant storage for these logs, it is possible to recover them when there is a failure in the auditing systems. Access permissions to these logs must be restricted to privileged users. Also log audit log access to help in identifying unintended access to audit data.

Suggestion 6.4.1 - Ensure that auditing is active in analytics services and are delivered to fault-tolerant persistent storage

Review the available audit log features of your analytics solutions, and configure the solutions to store the audit logs to a fault-tolerant persistent storage. It is to ensure that you have complete audit logs for security and compliance purposes.

For more details, refer to the following documentation:

- AWS Management & Governance Blog: AWS CloudTrail Best Practices
- Amazon Redshift Cluster Management Guide: Database audit logging
- Amazon OpenSearch Service (successor to Amazon Elasticsearch Service) Developer Guide: Monitoring audit logs in Amazon OpenSearch Service
- AWS Technical Guide - Build a Secure Enterprise Machine Learning Platform on AWS: Audit trail management
- AWS Big Data Blog: Build, secure, and manage data lakes with AWS Lake Formation

Reliability

The reliability pillar includes the ability of a system to recover from infrastructure or service disruptions, dynamically acquire computing resources to meet demand, and mitigate disruptions such as misconfiguration or transient network issues. It also includes the ability to understand the full travel path and change history of the data and keep the data safe when storage failure occurs.

7 - Design resiliency for analytics workload

How do you design analytics workloads to withstand failures? Every extract, transform, and load (ETL) job has corresponding business requirements, such as providing daily, weekly, or monthly sales flash reports. The analytics workload should meet the business SLAs by designing the ETL pipelines, data storage and metadata catalog to be resilient from failure.

ID	Priority	Best Practice
☐ BP 7.1	Required	Understand the business requirements of analytics and ETL jobs
☐ BP 7.2	Required	Monitor analytics systems to detect analytics or ETL job failures
☐ BP 7.3	Required	Notify stakeholders about analytics or ETL job failures
☐ BP 7.4	Recommended	Automate the recovery of analytics and ETL job failures
☐ BP 7.5	Recommended	Build a disaster recovery (DR) plan for the analytics infrastructure and the data

For more details, refer to the following documentation:

- AWS Glue Developer Guide: Running and Monitoring AWS Glue
- AWS Glue Developer Guide: Monitoring with Amazon CloudWatch
- AWS Glue Developer Guide: Monitoring AWS Glue Using Amazon CloudWatch Metrics
- AWS Prescriptive Guidance - Patterns: Orchestrate an ETL pipeline with validation, transformation, and partitioning using AWS Step Functions
- AWS Premium Support Knowledge Center: How can I use a Lambda function to receive SNS alerts when an AWS Glue job fails a retry?
- AWS Glue Developer Guide: Repairing and Resuming a Workflow Run
- AWS Data Pipeline Developer Guide: Cascading Failures and Reruns

Best Practice 7.1 - Understand the business requirements of analytics and ETL jobs

The business requirements and the service level agreements (SLAs) of analytics and ETL jobs will define how quickly jobs need to recover from failures. Determine the behavior of the job reruns, such as replacing or appending to existing data in the data repository.

Suggestion 7.1.1 - Understand the SLA of each ETL job, such as daily batch vs. real-time streaming pipeline

Each analytics job will have different delivery requirements based on the agreement with business stakeholders. Recognize the agreed delivery time or duration each job must meet for the proper business function.

Suggestion 7.1.2 - Identify system dependencies and the upstream and downstream workloads of the analytics and ETL jobs

Analytics systems often have multiple dependent upstream and downstream components that must function together for successful outcomes. Identify the analytics system dependencies, such as source data systems, intermediate processing, or report generation services that could impact the end-to-end delivery of the analytics job.

Suggestion 7.1.3 - Understand the impact to downstream workloads if the pipeline fails

Measure the impact of any component of the analytics system failure. You can test the overall impact from the failure of individual components by intentionally making reversible changes, such as temporarily removing authorization to dependent systems from the component's IAM role policy.

Suggestion 7.1.4 - Design the job recovery solution based on the delivery SLA

When practical, build systems that can meet SLA requirements even if jobs must be retried or manually recovered. If it's not practical to build systems that can recover within the SLA, ensure fail-back methods provide information that SLAs will not be met. For example, instead of a daily report arriving by email at 6am, provide an email notice that the daily report will not be delivered that day.

Best Practice 7.2 - Monitor analytics systems to detect analytics or ETL job failures

Detect job failures as soon as possible. Pinpointing where and how the error occurred is critical for notifications and corrective actions.

Suggestion 7.2.1 - Monitor and track jobs error from different levels, including infrastructure, ETL workflow, and ETL application code

Failures can occur at all levels of the analytics system. Each component in the analytics system should be instrumented to provide metrics indicating the health of the component. Monitor the emitted metrics and alarm if any components fail.

Suggestion 7.2.2 - Establish end-to-end monitoring for the complete analytics and ETL pipeline

End-to-end monitoring allows tracking the flow of data as it passes through the analytics system. In many cases, data processing might be dependent on application logic, such as sampling a subset of data from a data stream to check accuracy. Properly identifying and monitoring the end-to-end flow of data allows detecting at which step the analytics and ETL job fails.

Suggestions 7.2.3 - Determine what data was processed when the job failed

Failures in data processing systems can cause data integrity or data quality issues. Determine what data was being processed at the time of failure and perform quality checks of both the input and output data.

Suggestions 7.2.4 - Classify the severity of the job failures based on the type of failure and the business impact

Classifying the severity of different job failures will help you prioritize remediation and guide the notification requirements to key stakeholders.

Best Practice 7.3 - Notify stakeholders about analytics or ETL job failures

Analytics and ETL job failures can impact the SLAs for delivering the data on time for downstream analytics workloads. Failures might cause data quality or data integrity issues as well. Notifying all stakeholders, such as IT operations, help desk, data source, analytics, and downstream workloads, about the job failure as soon as possible is important for remediation actions needed.

Suggestions 7.3.1 - Establish automated notifications to predefined recipients

Use services such Amazon Simple Notification Service (Amazon SNS) to automatically send emails, phone alerts, or both in the event of failure.

Suggestions 7.3.2 – Do not include sensitive data in notifications

Automated alerts often include indicators of useful information for troubleshooting the failure. Ensure sensitive information, such as medical or financial information, is not shared in failure notifications.

Suggestions 7.3.3 - Integrate the analytics job failure notification solution with the enterprise operation management system

Where possible, integrate automated notifications into existing operations management tools. For example, an operations support ticket can be automatically filed in the event of a failure, and that same ticket can automatically be resolved if the analytics system recovers on retry.

Suggestions 7.3.4 – Notify IT operations and help desk teams of any ETL job failures

Normally, the IT operations team should be the first contact for production workload failures. The IT operations team will troubleshoot and attempt to recover the failed job, if possible. It is also helpful to notify the IT help desk for system failures that have end user impact, such as an issue with the data warehouse used by the business intelligence (BI) analysts.

Best Practice 7.4 - Automate the recovery of analytics and ETL job failures

Many factors can cause analytics and ETL job to fail. Some types of job failures can be recovered using automated recovery solutions. Designing and implementing an automated recovery solution will help reduce the impact of the job failures and streamline IT operations.

Suggestions 7.4.1 - Determine what types of job failures can be recovered safely using an automated recovery solution

Some failures can be remediated by rerunning the job differently with understanding of the failure type using application logic. Identify failure types, the root cause of each type of failure, and whether automation can be used to recover from failure.

Suggestions 7.4.2 - Design an automated recovery solution to handle different types of failures

For example:

- Configure automatic retries to handle intermittent network disruptions
- Set up a load-based automatic scaling policy to scale the compute environment to handle failures caused by throttling

Suggestions 7.4.3 - Limit the number of automatic reruns and create log entries for the automatic recovery attempts and results

Track the number of reruns an automated recovery can attempt. Limit the number of reruns to avoid wasting time and resources. Log recovery attempts and outcomes to drive future improvements of the automated recovery system.

Best Practice 7.5 - Build a disaster recovery (DR) plan for the analytics infrastructure and the data

Discuss with business stakeholders to confirm how fast the analytics systems should be recovered (the Recovery Time Objective or RTO) and what amount data loss is tolerable (the Recovery Point Objective or RPO) in a disaster recovery (DR) scenario. Depending on the business requirements, an analytics workload should be able to recover the systems and secure the data from AZ-wide or Region-wide failures.

Suggestion 7.5.1 – Confirm the business requirement of the disaster recovery (DR) plan

Speak to the business shareholders that the analytics workload serves, and identify their disaster recovery (DR) requirements of the data, metadata catalog and ETL pipelines based on the business requirements, data classification, legal and compliance requirements. Define the RTO and RPO for your data, metadata, and ETL pipelines.

Suggestion 7.5.2 - Design the disaster recovery (DR) solution

Review the architecture for your data and analytics pipeline and select the DR pattern that meets your DR requirements.

Suggestion 7.5.3 - Implement and test your backup solution based on the RPO and RTO

Backup solutions must be implemented to meet the RPO and RTO requirements. Periodically test your backup and restore solution to ensure that your RPO and RTO can be met.

8 - Govern data and metadata changes

How do you govern data and metadata changes? Controlled changes are not only necessary for infrastructure, but also required for data quality assurance. If the data changes are uncontrolled, it becomes difficult to anticipate the impact of these changes. It even makes downstream systems harder to manage data quality issues of their own.

ID	Priority	Best Practice
☐ BP 8.1	Required	Build a central Data Catalog to store, share, and track metadata changes
☐ BP 8.2	Required	Monitor for data quality anomalies
☐ BP 8.3	Required	Trace the data lineage

Best Practice 8.1 - Build a central Data Catalog to store, share, and track metadata changes

Building a central Data Catalog to store, share, and manage metadata across the organization is an integral part of data governance. This will promote standardization and reuse. Tracing metadata change history in the central Data Catalog helps you manage and control version changes in the metadata, and is often required for auditing and compliance.

Suggestion 8.1.1 - Changes on the metadata in the Data Catalog should be controlled and versioned

Use the Data Catalog change tracking features. For example, when the schema changes, AWS Glue Data Catalog will track the version change. You can use AWS Glue to compare schema versions, if needed. In addition, we recommend a change control process that only allows those authorized to make schema changes in your Data Catalog.

Best Practice 8.2 - Monitor for data quality anomalies

Good data quality is critical to the downstream data workloads and data consumers. Bad data will impact the accuracy of the decision-making activities, such as analytics insights and ML predictions. It will reduce the return on investment (ROI) and confidence of the data and analytics program. Monitor data quality and detect data anomalies as early as possible.

Suggestion 8.2.1 – Include a data quality check stage in the ETL pipeline as early as possible

A data quality check helps ensure that bad data is identified and fixed as soon as possible and prevent bad data from propagating downstream.

Suggestion 8.2.2 – Understand the nature of your data and determine the types of data anomalies need to be monitored and fixed based on the business requirements

The analytics workload may process various types of data such as structured, unstructured, picture, audio, and video formats. Some data may arrive to the workload periodically, or some may constantly

arrive in real time. It is pragmatic to assume that data does not always arrive to the analytics workload in perfect shape. And only a portion – not the whole set – of data matters to your workload.

You may need to understand the characteristics of data, and determine what forms of data anomaly you want to care. For example, if you expect the data always contain important attribute like customer ID, you can define that a data is abnormal if it doesn't contain `customer_id` attribute. Common data anomalies include duplicate data, missing data, incomplete data, incorrect data format, and different measurement units.

Suggestion 8.2.3 – Select an existing data quality solution or develop your own based on the requirements

For example, some data quality solutions can only detect single field data quality issues, while others can handle complex stateful data quality issues related to multiple fields.

Best Practice 8.3 - Trace the data lineage

Fully understanding where the data comes from, where it has been, how it's been transformed, who uses it, and how it's used is critical to getting real business value from the data. To achieve this goal, data lineage should be tracked, managed, and visualized. Ensure that the data lineage is captured to create this visibility, which can help simplify tracing errors back to the root cause in a data analytics process.

Suggestion 8.3.1 – Track and control data lineage information

Data lineage information includes where the data comes from, where it has been, how it's been transformed, and who uses it. Store the collected information in a persistent data store, such as Amazon S3, Amazon RDS, or Amazon DynamoDB.

Suggestion 8.3.2 – Implement steps in the ETL pipeline to check and validate record counts for each data movement and transformation

Perform basic validation of the records processed against expected output.

Suggestion 8.3.3 – Use visualization tools to investigate data lineage

Data lineage can become complicated when multiple systems are interacting with each another. Building a data lineage tool to visually investigate data lineage can drastically reduce troubleshooting time and help identify downstream impacts from bad data.

Suggestion 8.3.4 – Build a data lineage report to satisfy compliance and audit requirements

Build tools to generate data lineage reports as needed for compliance or audit purposes.

Performance efficiency

The performance efficiency pillar focuses on the efficient use of computing resources to meet requirements and the maintenance of that efficiency as demand changes and technologies evolve. Remember, performance optimization is not a one-time activity. It is an incremental and continual process of confirming business requirements, measuring the workload performance, identifying under-performing components, and tuning the components to meet your business needs.

9 - Choose the best-performing compute solution

How do you select the best-performing compute options for your analytics workload? The definition of best-performing will mean different things to different stakeholders, so gathering all stakeholders' input in the decision process is key. Define performance and cost goals by balancing business and

application requirements, then evaluate the overall efficiency of the compute solution against those goals using metrics emitted from the solution.

ID	Priority	Best Practice
☐ BP 9.1	Highly Recommended	Let business stakeholders confirm the business performance criteria of analytics processing
☐ BP 9.2	Highly Recommended	Choose analytics and ETL solutions that achieve the business purpose within operations constraints
☐ BP 9.3	Highly Recommended	Provision the compute resources to the location of the data storage
☐ BP 9.4	Recommended	Define and measure the computing performance metrics
☐ BP 9.5	Recommended	Periodically identify under-performing components and fine-tune the infrastructure or application logic

- AWS Whitepaper - Overview of Amazon Web Services: Analytics
- AWS Big Data Blog: Building high-quality benchmark tests for Amazon Redshift using Apache JMeter
- AWS Big Data Blog: Top 10 performance tuning techniques for Amazon Redshift

Best Practice 9.1 - Let business stakeholders confirm the business performance criteria of analytics processing

Performance optimization should start with your customer: the business users of the analytics workload. Let the business stakeholders define the performance requirements, then determine the computing requirements needed to meet their performance needs. For example, if the business needs a daily sales report, you might choose Amazon Redshift as the computing option along with running a periodic SQL query using CloudWatch Events and AWS Lambda. However, you should separate the computing requirements for data ingestion and data consumption. When a business user wants to ingest real-time streaming data into a data lake, another business user, who consumes the data, might only need periodic processing using daily or weekly jobs.

Suggestion 9.1.1 - Identify all stakeholders producing data for and consuming output from the analytics processing system

For each stakeholder, collect feedback on their business requirement metrics for analytics processing performance, such as duration-to-completely-process, or time-of-day deliverable deadlines.

Best Practice 9.2 - Choose analytics and ETL solutions that achieve the business purpose within operations constraints

AWS has multiple analytics processing services that are built for specific purposes, such as Amazon Athena, Amazon Redshift, Amazon EMR, Amazon CloudSearch, Amazon OpenSearch Service, Amazon Kinesis, Amazon QuickSight, AWS Data Exchange, AWS Glue, AWS Lake Formation, Amazon Managed Streaming for Apache Kafka (Amazon MSK), AWS Glue DataBrew, Amazon FinSpace, and so on. In general, consider each step of the data analytics process as another opportunity to find the right fit of functionality and performance. This allows you to select the right tools for the job and provision sufficient resources to meet the business requirements for an optimum overall solution.

Suggestion 9.2.1 – Identify the most constrained requirements based on the collected business metrics

Select services such that the most constrained requirements will be met. Where possible, select horizontally scalable architectures that allow the systems to respond to growing and shrinking demand while meeting processing requirements of the business.

Best Practice 9.3 - Provision the compute resources to the location of the data storage

In most cases, data analytics workloads require moving data through a pipeline, either for ingesting data, processing intermediate results, or producing curated datasets. It is easier and more efficient to select the location of data processing services near where the data is stored, rather than frequently copying or streaming large amounts of data to the processing location. For example, if an Amazon Redshift cluster frequently ingests data from a data lake, ensure that the Amazon Redshift cluster is in the same Region as your data lake S3 buckets.

Suggestion 9.3.1 - Migrate or copy primary data stores from on-premises environments to AWS so that cloud compute and storage are closely located

Avoid repeatedly transferring the same datasets from on-premises data stores to the cloud. Instead, create copies of your data near the analytics platform to avoid data transfer latency and improve overall performance of the analytics solution. Similarly, if data resides in a different AWS Region from the analytics systems, move either the analytics systems or the data to the same Region.

Suggestion 9.3.2 - Place data processing resources in the same AWS Region as the primary data stores

In some cases where data is stored within an AWS Region, you might also choose to locate the processing resources within the same AWS Region.

Best Practice 9.4 - Define and measure the computing performance metrics

Define how you will measure performance of the analytics solutions for each step in the process. For example, if the computing solution is a transient Amazon EMR cluster, you can define the performance as the Amazon EMR job runtime from the launch of the EMR cluster, processing the job, then shutting down the cluster. As another example, if the computing solution is an Amazon Redshift cluster that is shared by a business unit, you would need to define the performance as the runtime duration for each SQL query.

Suggestion 9.4.1 - Define performance efficiency metrics

Collect and use metrics to scale the resources needed to meet business requirements. Inform downstream processes or stakeholders of data delays or errors.

Best Practice 9.5 - Periodically identify under-performing components and fine-tune the infrastructure or application logic

After you have defined the performance measurement, you should identify which infrastructure components or jobs are running below the performance criteria. The performance fine-tuning will vary per AWS service. For example, if it is an Amazon EMR cluster, you would need to change to a larger cluster instance type, or increase the number of cluster nodes. However, for an Amazon Redshift cluster, you would either need to increase the number of cluster nodes to increase parallel computing capacity, or you would need to fine-tune the SQL queries that are running below the performance criteria.

Suggestion 9.5.1 - Evaluate your metrics performance during regular operational reviews

Take actions to properly configure your resources to meet the business requirements.

10 - Choose the best-performing storage solution

How do you select the best-performing storage options for your workload? An analytics workload's optimal storage solution is determined by various aspects such as compute engine (Amazon EMR, Amazon Redshift, Amazon RDS, etc.), access patterns (random or sequential), required throughput, access frequency (online, offline, archival), update patterns (append only, in-place update), and availability and durability requirements. Choose the best-performing storage solution for your analytics workload's own characteristics.

ID	Priority	Best Practice
☐ BP 10.1	Highly Recommended	Identify critical performance criteria of storage for the workload: I/O latency, I/O throughput, or data size growth
☐ BP 10.2	Highly Recommended	Evaluate and confirm the available storage options per compute solution of your choice
☐ BP 10.3	Recommended	Choose the optimal storage based on access patterns, data growth, and the performance metrics

For more details, refer to the following documentation:

- Amazon Elastic Compute Cloud User Guide for Linux Instances: Amazon EBS volume types
- Amazon Redshift Database Developer Guide: Amazon Redshift best practices for loading data PDF
- Amazon EMR Management Guide: Instance storage
- Amazon Simple Storage Service User Guide: Best practices design patterns: optimizing Amazon S3 performance

Best Practice 10.1 - Identify critical performance criteria of storage for the workload: I/O latency, I/O throughput, or data size growth

In large data analytics workloads, data input/output (I/O) is often a constraining factor. To achieve the performance efficiency of the overall solution, determine whether bottlenecks in the process are bound by the compute performance or the storage performance. When storage performance is a bottleneck, determine the necessary performance criteria is met by the storage solution.

Suggestion 10.1.1 - Use CloudWatch metrics or self-managed performance monitoring tools to determine if the analytics system performance is limited by CPU or I/O

Use a metric collection and reporting system, such as Amazon CloudWatch, to analyze the performance characteristics of the analytics system. Evaluate the measured performance metrics relative to system reference documentation to characterize the system constraints for the workload as a percentage of maximum performance. Evaluate network throughput, data storage throughput/IOPS, CPU utilization, and other relevant metrics to the workload.

Best Practice 10.2 - Evaluate and confirm the available storage options for your compute solution

Many AWS data analytics services allow you to use more than one type of storage. For example, Amazon Redshift allows access to data stored in the compute nodes in addition to data stored in Amazon

S3. When performing research on each data analytics service, evaluate all of the storage options to determine the most performance efficient solution that meets business requirements.

Suggestion 10.2.1 - Review the available storage options for the analytics services being considered

For example, Amazon EMR provides local storage via HDFS file system and S3 as an external storage via EMRFS. For more information, refer to the AWS documentations for your compute solution:

- Amazon EMR Management Guide: Work with storage and file systems
- Amazon Redshift Cluster Management Guide: Overview of Amazon Redshift clusters
- Amazon OpenSearch Service (successor to Amazon Elasticsearch Service) Developer Guide: Managing indices in Amazon OpenSearch Service
- Amazon Aurora User Guide: Overview of Aurora storage

Suggestion 10.2.2 - Evaluate the performance of the selected storage option

Evaluate the performance by running simulated real-world scale testing to ensure that the overall analytics system design meets requirements.

Best Practice 10.3 - Choose the optimal storage based on access patterns, data growth, and the performance metrics

Storage options for data analytics can have performance tradeoffs based on access patterns and data size. For example, in Amazon S3 it is much more efficient to retrieve a single 200GB compressed object containing many small 1 KB log lines than it is to retrieve millions of individual 1 KB log objects. Evaluate your workload needs and usage patterns to determine if the method or location of storing your data can improve the overall efficiency of your solution.

Suggestion 10.3.1 – Identify available solution options for the performance improvement

When data I/O is limiting performance and business requirements are not being met, improve I/O through the options available within that service. For example, with EBS volumes of GP3 type, increase Provisioned IOPS or throughput, or for Amazon Redshift, increase the number of nodes.

11 - Choose the best-performing file format and partitioning

How do you select the best-performing file formats and partitioning? Selecting the best-performing file format and partitioning of data at rest can have a large impact on the overall analytics workload efficiency. Optimize the performance of the analytics workload by storing data with the use case in mind. Also choose the right data compression format and use data partitioning according to the data access patterns of the analytics workload.

ID	Priority	Best Practice
☐ BP 11.1	Highly Recommended	Select format based on data write frequency and patterns (append-only vs. in-place update)
☐ BP 11.2	Highly Recommended	Select format based on data read frequency and patterns
☐ BP 11.3	Recommended	Use file compression to reduce number of files and to improve file I/O efficiency
☐ BP 11.4	Recommended	Partition the data to avoid unnecessary file reads

For more details, refer to the following documentation:

- Amazon Redshift Database Developer Guide: Creating data files for queries in Amazon Redshift Spectrum
- Amazon EMR Release Guide: Hudi
- AWS Big Data Blog: Apply record level changes from relational databases to Amazon S3 data lake using Apache Hudi on Amazon EMR and AWS Database Migration Service

Best Practice 11.1 - Select format based on data write frequency and patterns (append-only vs. in-place update)

Evaluate your data storage access patterns and performance requirements. For example, for a streaming data ingestion case, instead of storing many small data files individually, periodically batch-process the small files into a single larger compressed file, which will be more performant upon retrieval.

Suggestion 11.1.1 - Understand your analytics workload data write characteristics

If storing data in Amazon S3, evaluate if an append-only method such as Apache Hudi is right for your needs. Where practical, use batched write updates.

Best Practice 11.2 - Select format based on data read frequency and patterns

Evaluate how frequently data is retrieved and move it to an appropriate tier based on performance. For example, you can find which data is access by looking at query patterns such as `SELECT … FROM … WHERE … GROUP BY ….` Or, offloading historical, infrequently-accessed data to Amazon S3 in a compressed file format allows querying with Amazon Redshift Spectrum while keeping frequently accessed data in the data warehouse.

Suggestion 11.2.1 - Understand your analytics workload data read characteristics and patterns

Select the storage service that meets the performance requirements while maintaining SLAs.

Suggestion 11.2.2 - Be aware of API-driven data access pattern constraints, such as the amount of data retrieved per API request, which could impact overall performance due to API throttling

Refer to AWS documentation for API quotas per service.

Suggestion 11.2.3 - Use caching services to improve performance and reduce reads from the storage tier

Caching services can speed up the responses to common queries and reduce the load on the storage tier. Use Amazon ElastiCache, Amazon DynamoDB Accelerator (DAX), API Gateway caching, or other relevant caching services.

Best Practice 11.3 - Use file compression to reduce number of files and to improve file I/O efficiency

If possible, store data in a compressed format to reduce I/O burden on the underlying storage host and network. For example, for columnar data stored in Amazon S3, use a compatible compression algorithm that supports parallel reads, such as bzip2.

Suggestion 11.3.1 - Understand the I/O constraints on the workload

Measure the I/O characteristics of the workload. Determine I/O constraints by evaluating all aspects of the workload, including data retrieval, decompression, data processing, compression, and data storage.

Suggestion 11.3.2 – Compress data to reduce the transfer time

When storage read/write performance is a bottleneck, use compression to reduce data transfer time. Consider if the compute requirements to perform compression and decompression overcomes the storage I/O bottleneck and improves overall performance efficiency.

Suggestion 11.3.3 – Evaluate the available compression options for each resource of the workload

For each service used in the workload, evaluate the compression options available.

Best Practice 11.4 - Partition the data to avoid unnecessary file reads

If possible, store data in structured partitions, which allows the compute to identify the location of only those portions of the data relevant for the query. Determine the most frequent query parameters and store the data appropriately for the data retrieval needs. For example, if an analytics workload regularly generates daily, weekly, and monthly reports, store data partitioned with year/month/day format.

Suggestion 11.4.1 - Store data partitioned based on column with incremental processing constraints

This partitioning scheme is most often used with data processing needed for different time windows, such as daily, weekly, or monthly reports.

Suggestion 11.4.2 - Store data partitioned based on reducing number of files or compaction

Store frequently-accessed data ('hot' data) and barely-accessed data ('cold' data) into separate partitions. For example, if you have to archive data for regulatory reasons, you can store the data into S3 bucket with a prefix such as /archive, and you can configure a S3 life cycle policy to automatically move it into Amazon S3 Glacier. Or, when you have too many small files to process, you can consolidate such small files into a S3 bucket with a prefix such as /raw-data, and you can generate a pre-processed, big-size-but-less-number of files into a S3 bucket with /pre-processed prefix for faster analytical processing upon the pre-processed files.

Suggestion 11.4.3 - Store data partitioned based on columns frequently used in queries for filtering

This partitioning scheme is most often used with data stored in many columns and retrieval of all columns is unnecessary.

Suggestion 11.4.4 - Store data partitioned based on time attributes with earlier data in infrequent-access tiers

Use the tiering capabilities of the storage service to put infrequently accessed data in the tier appropriate for the workload. For example, in the Amazon Redshift data warehouse, infrequently accessed data can be stored in Amazon S3 and queried with Redshift Spectrum, while frequently accessed data can be stored in local Amazon Redshift storage.

Cost optimization

The cost optimization pillar includes the continual process of refinement and improvement of a system over its entire lifecycle to optimize cost, from the initial design of your first proof of concept to the ongoing operation of production workloads. It's a years-long, continual process. Choose the right solution and pricing model. Build cost-aware systems that allow you to achieve business outcomes and minimize costs. To perform cost optimization over time, you need to identify data, infrastructure resources, and analytics jobs that can be removed or downsized.

Determine the analytics workflow costs at each individual data processing step or individual pipeline branch. The benefit of understanding analytics workflow costs at this granular level will help you

decide where to focus engineering resources for development, and perform return on investment (ROI) calculations for the analytics portfolio as a whole.

12 - Choose cost-effective compute and storage solutions based on workload usage patterns

How do you select the compute and storage solution for your analytics workload? Your initial design choice could have significant cost impact. Understand the resource requirements of your workload, including its steady-state and spikiness, and then select the solution and tools that meet your requirements. Avoid over-provisioning to allow more cost optimization opportunities.

ID	Priority	Best Practice
☐ BP 12.1	Recommended	Decouple storage from compute
☐ BP 12.2	Recommended	Plan and provision capacity for predictable workload usage
☐ BP 12.3	Recommended	Use On-Demand Instance capacity for unpredictable workload usage
☐ BP 12.4	Recommended	Avoid data duplication

For more details, refer to the following documentation:

- Amazon Elastic Compute Cloud User Guide for Linux Instances: Get recommendations for an instance type
- AWS Cost Management & Optimization - AWS Cost Optimization: Right Sizing
- AWS Whitepaper - Right Sizing: Provisioning Instances to Match Workloads: Tips for Right Sizing

Best Practice 12.1 - Decouple storage from compute

It's common for data assets to grow exponentially year over year. However, your compute needs might not grow at the same rate. Decoupling storage from compute allows you to manage cost of storage and compute separately, and implement different cost optimization features to minimize cost.

Suggestion 12.1.1 - Compress data when applicable

Most analytics services can access compressed data. Compressing your data, and storing data in columnar formats, can improve query speed in addition to reduce the cost of query transactions.

Suggestion 12.1.2 - Consider data temperature when choosing data store and storage class

Tiered storage transitions datasets to different storage tiers based on their usage patterns to optimize storage cost. Amazon S3 offers a variety of storage classes that allow you to optimize costs over time. Consider a lifecycle plan that migrates data from S3 Standard to S3-Infrequent Access (or in some cases S3-Infrequent Access Single-AZ) to Amazon S3 Glacier to be a sufficient cost-savings measure.

Suggestion 12.1.3 - Use low-cost compute resources, such as Spot Instances, when applicable

Decouple storage from compute allows stateless logic implementation, consider using Amazon EC2 Spot Instances for additional cost savings. Spot Instances are also an excellent option for reducing costs for development or quality assurance (QA) applications.

Suggestion 12.1.4 - Deploy compute close to data to reduce data transfer cost

In AWS, data transfer charges apply to data transferred out of AWS to the internet or over Direct Connect, data transferred between AWS Regions, and data transferred between Availability Zones. Data transfer into AWS and data transfer within an AZ is at no cost.

Suggestion 12.1.5 - Use Amazon S3 Select and Amazon S3 Glacier Select to reduce data retrieval

Amazon S3 Select and Amazon S3 Glacier Select allow applications to retrieve only a subset of data from an object by using simple SQL expressions.

Best Practice 12.2 - Plan and provision capacity for predictable workload usage

For well-defined workloads, planning capacity ahead based on average usage pattern helps improve resource utilization and avoid over provisioning. For a spiky workload, set up automatic scaling to meet user and workload demand.

Suggestion 12.2.1 - Choose the right instance type based on workload pattern and growth ratio

Consider resource needs, such as CPU, memory, and networking, that meet the performance requirements of your workload. Choose the right instance type and avoid over provisioning. An optimized EC2 instance runs your workloads with optimal performance and infrastructure cost. For instance, choose the smaller instance if your growth ratio is low as this allows more granular incremental change.

Suggestion 12.2.2 – Choose the right sizing based on average or medium workload usage

Right sizing is the process of matching instance types and sizes to your workload performance and capacity requirements at the lowest possible cost. It's also the process of looking at deployed instances and identifying opportunities to downsize without compromising capacity or other requirements, which will result in lower costs.

Suggestion 12.2.3 - Use automatic scaling capability to meet the peak demand instead of over provisioning

Many analytics system components can scale dynamically to meet demand. When possible, architect your analytics system to use horizontal scaling instead of vertical scaling.

Best Practice 12.3 - Use On-Demand Instance capacity for unpredictable workload usage

Serverless solutions are either charged by the amount of data processed or the compute resource used, but only when there is a workload actively running. Compare this approach to using long running infrastructure, but where you don't need to pay for idle resources.

Suggestion 12.3.1 - Use Amazon Athena for ad hoc SQL workloads

Amazon Athena is a serverless query service that makes it easy to analyze data directly in Amazon S3 using standard SQL. With Amazon Athena, you only pay for the queries that you run. You are charged based on the amount of data scanned per query.

Suggestion 12.3.2 - Use AWS Glue instead of Amazon EMR for infrequent ETL jobs

AWS Glue is a fully managed ETL (extract, transform, and load) service that makes it simple and cost-effective to categorize your data, clean it, enrich it, and move it reliably between various data stores and data streams. With AWS Glue jobs, you pay only for the resources used during the ETL process. In contrast, Amazon EMR is typically used for frequently running jobs requiring semi-persistent data storage.

Suggestion 12.3.3 - Use on-demand resources for transient workloads or short-term development and testing need

Use on-demand resources such as Amazon EMR on EC2 Spot Instances to perform experimental or test data processing with low cost. During the initial planning and testing phases of analytics workloads, using on-demand resources provides flexibility to iterate through many alternative architectures until all aspects of a well-architected analytics project are optimized for the job, such as selecting the right instance type or using a serverless architecture to meet the required time-duration of analytics pipeline runs.

Best Practice 12.4 - Avoid data duplication

Teams want to share data at many levels to allow broad and deep insights but also to minimize complexity and cost. For example, data needs to be shared from a central data warehouse that loads and transforms constant streams of updates with BI and analytics clusters that serve a variety of workloads, such as dashboard applications, ad hoc queries, and data science. But unloading data from one system (the producer) and copying it into another (the consumer) can be expensive and introduce delays, especially as the number of consumers grow. This approach requires building and maintaining separate ETL jobs to provide relevant subsets of the data for each consumer. The complexity increases with the security practices that must be followed to regularly monitor business-critical data usage and ensure compliance. Thus, analytics workloads should adopt technical solutions that allow data sharing without data duplication whenever possible.

Suggestion 12.4.1 - Implement a central storage layer to share data among tenants

A centralized storage layer, such as a data lake architecture, can be used to make the same data resources available to different teams. Security isolations can be enforced so that only relevant subsets of data are made available to teams that must have access to those portions of the data lake. Use a solution such as AWS Lake Formation to build a secure data lake.

13 - Manage cost over time

How do you manage the cost of your workload over time? To ensure that you always have the most cost-efficient workload, periodically review your workload to discover opportunities to implement new services, features, and components. It is common for analytics workloads to have an ever-growing number of users and exponential growth of data volume. You should implement a standardized process across your organization to identify and remove unused resources, such as unused data, infrastructure, and ETL jobs. Do not forget to notify downstream system owners of any deletions, so that they can anticipate impacts to their systems.

ID	Priority	Best Practice
☐ BP 13.1	Recommended	Delete unused data, infrastructure, or jobs
☐ BP 13.2	Recommended	Reduce the use of over-provisioned infrastructure
☐ BP 13.3	Recommended	Reduce repeating analytics jobs with no business value
☐ BP 13.4	Recommended	Evaluate and adopt new cost-effective solutions

For more details, refer to the following documentation:

- AWS Database Blog: Safely reduce the cost of your unused Amazon DynamoDB tables using on-demand mode
- AWS Management & Governance Blog: Controlling your AWS costs by deleting unused Amazon EBS volumes

- AWS Database Blog: Implementing DB Instance Stop and Start in Amazon RDS
- AWS Big Data Blog: Lower your costs with the new pause and resume actions on Amazon Redshift
- AWS Partner Network (APN) Blog: Scaling Laravel Jobs with AWS Batch and Amazon EventBridge
- AWS Glue Developer Guide: Tracking Processed Data Using Job Bookmarks

Best Practice 13.1 - Delete unused data, infrastructure, or jobs

Delete data that is out of its retention period, or not needed anymore. Delete intermediate-processed data that can be removed without business impacts. If the output of analytics jobs is not used by anyone, consider removing such jobs so that you don't waste resources.

Suggestion 13.1.1 - Track data freshness

In many cases, maintaining a metadata repository for tracking data movement will be worthwhile, not only to instill confidence in the quality of the data, but also to identify infrequently updated data, and unused data.

Suggestion 13.1.2 - Delete data that is out of its retention period

Data that is past its retention period should be deleted to reduce unnecessary storage costs. Identify data through the metadata catalog that is outside its retention period. Automate the data removal process to reduce human effort. If data is stored in Amazon S3, use S3 lifecycle configurations to automatically expire data.

Suggestion 13.1.3 - Delete intermediate-processed data that can be removed without business impacts

Many steps in analytics processes create intermediate or temporary datasets. Ensure intermediate datasets are removed if they have no further business value.

Suggestion 13.1.4 - Delete unused analytics jobs that consume infrastructure resources but no one uses the job results

Periodically review the ownership, source, and downstream consumers of all analytics infrastructure resources. If downstream consumers no longer need the analytics job, stop the job from running and remove unneeded resources.

Best Practice 13.2 - Reduce the use of over-provisioned infrastructure

Workload resource utilization can change over time, especially after performance optimization. You should review resource usage patterns and determine if you still need the same infrastructure footprint to meet your business goals. Optimize your cost by removing the unneeded resources.

Suggestion 13.2.1 - Evaluate if compute resources can be downsized

Investigate your resource utilization by inspecting the metrics provided by Amazon CloudWatch. Evaluate if the resources can be downsized to one-level smaller within the same instance class, such as downsizing Amazon EMR cluster nodes from `m5.16xlarge` to `m5.12xlarge` .

Suggestion 13.2.2 - Move infrequently used data out of a data warehouse into a data lake

Data that is infrequently used can be moved from the data warehouse into the data lake to be queried in place or joined with data in the warehouse. Use services such as Redshift Spectrum to query and join data in the Amazon S3 data lake, or Amazon Athena to query data at rest in Amazon S3.

Suggestion 13.2.3 - Merge low utilization infrastructure resources

If you have several workloads that all have low-utilization resources, determine if you can combine those workloads to run on shared infrastructure. In many cases, using a pooled resource model for analytics workloads will save on infrastructure costs.

Suggestion 13.2.4 - Move infrequently accessed data into low-cost storage tiers

When designing a data lake or data analytics project, considerations such as required access patterns, transaction concurrency, and acceptable transaction latency will influence where data is stored. It is equally important to consider how often previous data will be accessed, and to have a data lifecycle plan to migrate data tiers from hotter storage to colder, less-expensive storage, while still meeting all business objectives.

Transitioning between storage tiers is achieved using Amazon S3 lifecycle policies, which automatically transitions objects into another tier with lower cost, or will even delete expired data. Amazon S3 Intelligent-Tiering will analyze the data access patterns and automatically move objects between tiers.

Best practice 13.3 - Reduce repeating analytics jobs with no business value

It is a common human behavior to expect frequently refreshed data. However, the frequency of running analytics jobs should be considered in the context of its business value. There is no need to refresh data repeatedly if the data is not used so frequently.

Suggestion 13.3.1 - Use the lowest acceptable frequency for data processing

Data processing requirements must be considered in the business context. There is no value in processing data faster than it will be consumed or delivered. For example, in a sales analytics workload, it might not be necessary to perform analytics on each transaction as it arrives when only hourly reports are needed by business management. In such a case, batch processing the transactions will be more efficient and can reduce unnecessary infrastructure costs between batch processing jobs.

Best Practice 13.4 - Evaluate and adopt new cost-effective solutions

As AWS releases new services and features, it's a best practice to review your existing architectural decisions to ensure that they remain cost effective. If a new or updated service can support the same workload but in a much cheaper way, consider implementing the change to reduce cost.

Suggestion 13.4.1 - Set service quotas to control resource usage

Some AWS services allow setting service quotas per account. Service quotas should be established to prevent runaway infrastructure deployment by accident. Ensure service quotas are set high enough to cover the expected peak usage.

Suggestion 13.4.2 – Pause and resume resources if the workload is not always required

Use automation to pause and resume resources when the resource is unneeded. For example, stop development and test Amazon RDS instances that are not used after working hours.

Suggestion 13.4.3 - Switch to a new service that is cheaper, for example, using Aurora Serverless instead of Amazon RDS

AWS is constantly adding new capabilities so you can leverage the latest technologies to experiment and innovate more quickly. Review new service releases frequently to understand the price and performance, as well as the purpose the service when it was released.

- What's New with AWS?

14 - Use optimal pricing models based on infrastructure usage patterns

How do you choose the financially-optimal pricing models of the infrastructure? Consult with your finance team and choose optimal purchasing options. such as On-Demand Instances, Reserved Instances, or Spot Instances. Once you understand the infrastructure usage patterns of the analytics workload, you can optimize the cost by purchasing reserved capacity with upfront payment, by using Spot Instances, or by paying Amazon EC2 usage via on-demand pricing models. Evaluate the available purchasing models of the analytics infrastructure of your choice and determine the optimal payment models.

ID	Priority	Best Practice
☐ BP 14.1	Recommended	Evaluate the infrastructure usage patterns then choose payment options accordingly
☐ BP 14.2	Recommended	Consult with your finance team and determine optimal payment models

For more details, refer to the following documentation:

- AWS Cloud Enterprise Strategy Blog: Managing Your Cost Savings with Amazon Reserved Instances
- AWS Big Data Blog: How Goodreads offloads Amazon DynamoDB tables to Amazon S3 and queries them using Amazon Athena
- AWS Big Data Blog: Best practices for resizing and automatic scaling in Amazon EMR
- AWS Big Data Blog: Work with partitioned data in AWS Glue
- AWS Big Data Blog: Using Amazon Redshift Spectrum, Amazon Athena, and AWS Glue with Node.js in Production
- AWS Compute Blog: 10 things you can do today to reduce AWS costs
- AWS Billing and Cost Management User Guide: Using Cost Allocation Tags
- AWS Well-Architected Framework: Cost Optimization Pillar
- AWS Whitepaper: Laying the Foundation: Setting Up Your Environment for Cost Optimization
- AWS Whitepaper: Amazon EC2 Reserved Instances and Other AWS Reservation Models
- AWS Whitepaper: Overview of Amazon EC2 Spot Instances
- AWS Whitepaper: Right Sizing: Provisioning Instances to Match Workloads
- AWS Whitepaper: AWS Storage Optimization

Best Practice 14.1 - Evaluate the infrastructure usage patterns, then choose your payment options accordingly

On-demand resources provides immense flexibility with pay-as-you-go payment models across multiple scenarios and scales. On the other hand, Reserved Instances provide significant cost saving for workloads that have steady resource utilization. Perform regular workload resource usage analysis. Choose the best pricing model to ensure that you don't miss cost optimization opportunities and maximize your discounts.

Suggestion 14.1.1 - Evaluate available payment options of the infrastructure resources of your choice

Review the pricing page for specific AWS services. Each service will list the billing metrics, such as runtime or gigabytes processed, as well as any discount options for dedicated usage. In addition, many AWS analytics services offer discounted payment terms, Reserved Instances or Savings Plans, in exchange

for a specific usage commitment. Almost all AWS services offer the payment for usage On-Demand, meaning you only pay for what you used.

Suggestion 14.1.2 - For steady, permanent workloads, obtain Reserved Instances or Savings Plans price discounts instead of paying on-demand pricing

Reserved Instances give you the option to reserve some AWS resources for a one- or three-year term and in turn receive a significant discount compared to the On-Demand Instance pricing. Workloads that have consistent long-term usage are good candidates for the Reserved Instance payment option.

Suggestion 14.1.3 - Use on-demand resources during development and in pre-production environments

Development and pre-production environments frequently change and often do not need to be always available. In cases where utilization is unpredictable, frequently changed, or only used for portions of the day, on-demand resources are the best option.

Best Practice 14.2 - Consult with your finance team and determine optimal payment models

If you use reserved-capacity pricing options, you can reduce the infrastructure cost without modifying your workload architectures. Collaborate with your finance team on the planning and use of purchase discounts. Make informed decisions regarding various factors, such as the amount of capacity to reserve, reserve term length, and the choice of upfront payments for their corresponding discount rates. The finance team should assist your team in determining the best long-term and reserved-capacity pricing options, because it affects your IT budget plans, such as which month is the right moment to pay an upfront charge.

Suggestion 14.2.1 - Consolidate the infrastructure usage to maximize the coverage of reserved capacity price options

Reserved Instances and Savings Plans purchases apply automatically to the resources that will receive the largest discount benefit. To maximize your discount utilization, consolidate resources in accounts within an AWS Organization structure. Allow the purchase commitments to apply to other AWS accounts within the Organization if they are unused in the account in which they are purchased.

Sustainability

The sustainability pillar includes the ability to continually improve sustainability impacts by reducing energy consumption and increasing efficiency across all components of a workload by maximizing the benefits from the provisioned resources and minimizing the total resources required.

There are no sustainability practices unique to this lens. For information on Sustainability, refer to the Sustainability Pillar whitepaper.

Scenarios

In this section, we cover the six key scenarios that are common in many analytics applications and how they influence the design and architecture of your analytics environment in AWS. We present the assumptions made for each of these scenarios, the common drivers for the design, and a reference architecture for how these scenarios should be implemented.

Scenarios

Modern data architecture (formerly Lake House)

Organizations have been building data lakes to analyze massive amounts of data for deeper insights into their data. To do this, they bring data from multiple silos into their data lake, and then run analytics and AI/ML directly on it. It is common for these organizations to also have data stored in specialized data stores, such as a NoSQL database, a search service, or a data warehouse, to support different use cases. To efficiently analyze all of the data spread across the data lake and other data stores, businesses often move data in and out of data lake and between these data stores. This data movement can get complex and messy as the data grows in these stores. To address this, businesses need a data architecture that not only allows building scalable, cost-effective data lakes but also supports simplified governance and data movement between various data stores. We refer to this as a *lake house* architecture. A *lake house* is a modern data architecture that integrates a data lake, a data warehouse, and other purpose-built data stores while enabling unified governance and seamless data movement.

As shown in the following diagram, with a lake house approach, organizations can store their data in a data lake and also be able to use purpose-built data stores that work with the data lake. This approach allows access to all of their data to make better decisions with agility.

Modern data architecture

In a lake house design, there are three different patterns for data movement. They can be described as follows:

Inside-out data movement: A subset of data in a data lake is sometimes moved to a data store, such as an Amazon OpenSearch Service cluster or an Amazon Neptune cluster, to support specialized analytics, such as search analytics, building knowledge graphs, or both. This pattern is what we consider an inside-out data movement. For example, enterprises send information from structured sources (relational databases), unstructured sources (metadata, media, or spreadsheets) and other assets first to a data lake that is moved to Amazon Neptune to build a knowledge graph.

Outside-in data movement: Organizations use data stores that best fit their applications and later move that data into a data lake for analytics. For instance, to maintain game state, player data, session history, and leaderboards, a gaming company right chooses Amazon DynamoDB as the data store. This data can later be exported to a data lake for additional analytics to improve the gaming experience for its players. We refer to this kind of data movement as outside-in.

Around the perimeter: In addition to the preceding two patterns, there are scenarios where the data is moved from one specialized data store to another. For example, enterprises might copy customer profile data from their relational database to a NoSQL database to support their reporting dashboards. This data movement is often considered as around the perimeter.

Characteristics

Scalable data lake: A data lake is at the center of a well-architected lake house design. A data lake should be able to scale easily to petabytes and exabytes as data grows. Use a scalable, durable data store that provides the fastest performance at the lowest cost, supports multiple ways to bring data in and has a good partner ecosystem.

Data diversity: Applications generate data in many formats. A data lake should support diverse data types — structured, semi-structured, or unstructured.

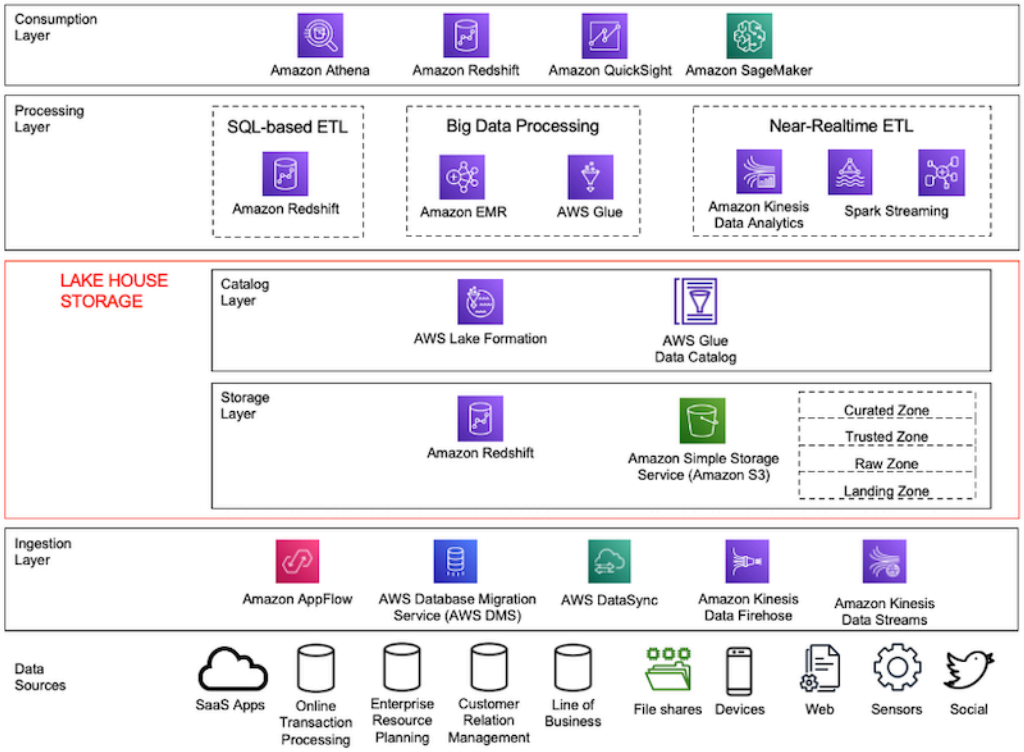
Schema management: A lake house design should support schema on read for a data lake with no strict source data requirement. The choice of storage structure, schema, ingestion frequency, and data quality should be left to the data producer. A data lake should also be able to incorporate changes to the structure of the incoming data, which is referred to as schema evolution. In addition, schema enforcement helps businesses ensure data quality by preventing writes that do not match the schema.

Metadata management: Data should be self-discoverable with the ability to track lineage as data flows through tiers within the data lake. A comprehensive data catalog that captures the metadata and provides a query-able interface for all data assets is recommended.

Unified governance: A lake house design should have a robust mechanism for centralized authorization and auditing. Configuring access policies in the data lake and across all the data stores can be extremely complex and error prone. Having a centralized location to define the policies and enforce them is critical to a secure lake house architecture.

Transactional semantics: In a data lake, data is often ingested nearly continuously from multiple sources and is queried concurrently by multiple analytic engines. Having atomic, consistent, isolated, and durable (ACID) transactions is pivotal to keeping data consistent.

Reference architecture



Modern data architecture reference architecture

Configuration notes

- To organize data for efficient access and easy management:
  - The storage layer can store data in different states of consumption readiness, including raw, trusted-conformed, enriched, and modeled. It's important to segment your data lake into landing, raw, trusted, and curated zones to store data depending on its consumption readiness. Typically, data is ingested and stored as is in the data lake (without having to first define schema) to accelerate ingestion and reduce time needed for preparation before data can be explored.
  - Partition data with keys that align to common query criteria.
  - Convert data to an open columnar file format, and apply compression. This will lower storage usage, and increase query performance.
- Choose the proper storage tier based on data temperature. Establish a data lifecycle policy to automatically delete old data to meet your retention requirements.
- Decide on a location for data lake ingestion (that is, an S3 bucket). Select a frequency and isolation mechanism that meets your business needs.
- Depending on your ingestion frequency or data mutation rate, schedule file compaction to maintain optimal performance.
- Use AWS Glue crawlers to discover new datasets, track lineage, and avoid a data swamp.
- Manage access control and security using AWS Lake Formation, IAM role setting, AWS KMS, and AWS CloudTrail.
- No need to move data between a data lake and the data warehouse for the data warehouse to access it. Amazon Redshift Spectrum can directly access the dataset in the data lake.
- For more, refer to the Derive Insights from AWS Lake House whitepaper.

Data mesh

Organizations of all sizes have recognized that data is one of the key factors for increasing and sustaining innovation, and driving value for their customers and business units. They are modernizing traditional data platforms with cloud-native technologies that are highly scalable, feature-rich, and cost-effective. As you look to make business decisions driven by data, you can be agile and productive by adopting a mindset that delivers data products from specialized teams, rather than through a centralized data management platform that provides generalized analytics.

A centralized model simplifies staffing and training by centralizing data and technical expertise in a single place. This reduces technical debt since you are managing a single data platform, which reduces operational costs. Data platform groups, often part of central IT, are divided into teams based on the technical functions they support. For instance, one team might own the ingestion technologies used to collect data from numerous data sources managed by other teams and lines of business (LOBs). A different team might own the data pipelines, the writing and debugging extract, transform, and load (ETL) code, and orchestrating job runs, while validating and fixing data quality issues and ensuring that data processing meets business SLAs. However, managing data through a central data platform can create scaling, ownership, and accountability challenges. Central teams might not understand the specific needs of a data domain, due to data types and storage, security, data catalog requirements, or the specific technologies needed for data processing.

You can often reduce these challenges by giving ownership and autonomy to the team who owns the data. This allows them to focus on building data products, rather than being limited to a common central data platform. For example, make product teams responsible for ensuring that the product inventory is updated regularly with new products and changes to existing ones. They're the domain experts of the product inventory datasets, and if a discrepancy occurs, they're the ones who know how to fix it. Therefore, they're best able to implement and operate a technical solution to ingest, process, and produce the product inventory dataset. They own everything leading up to the data being consumed: they choose the technology stack, operate in the mindset of data as a product, enforce security and auditing, and provide a mechanism to expose the data to the organization in an easy-to-consume way. This reduces overall friction for information flow in the organization, where the producer is responsible for the datasets they produce and is accountable to the consumer based on the advertised SLAs.

This data-as-a-product paradigm is similar to the operating model that Amazon uses for building services. Service teams build their services, expose APIs with advertised SLAs, operate their services, and own the end-to-end customer experience. This is distinct from the model where one team builds the software, and a different team operates it. The end-to-end ownership model has allowed us to implement faster, with higher efficiency, and to quickly scale to meet customers' use cases. We aren't limited by centralized teams and their ability to scale to meet the demands of the business. Each service we build relies on other services that provide the building blocks. The analogy to this approach in the data world would be the data producers owning the end-to-end implementation and serving of data products, using the technologies they selected based on their unique needs. At AWS, we have been talking about the data-driven organization model for years, which consists of data producers and consumers. This model is similar to those used by some of our customers and has been described by Zhamak Dehghani of Thoughtworks, who coined the term data mesh .

Characteristics

- Data mesh is a pattern for defining how organizations can organize around data domains with a focus on delivering data as a product. However, it might not be the right pattern for every customer.
- A lake house approach and the data lake architecture provide technical guidance and solutions for building a modern data platform on AWS.
- The lake house approach with a foundational data lake serves as a repeatable blueprint for implementing data domains and products in a scalable way.
- The manner in which you use AWS analytics services in a data mesh pattern might change over time, but remains consistent with the technological recommendations and best practices for each service.

The following are data mesh design goals:

- **Data as a product** – Each organizational domain owns their data end to end. They're responsible for building, operating, serving, and resolving any issues arising from the use of their data. Data accuracy and accountability lies with the data owner within the domain.
- **Federated data governance** – Data governance helps ensure that data is secure, accurate, and not misused. The technical implementation of data governance, such as collecting lineage, validating data quality, encrypting data at rest and in transit, and enforcing appropriate access controls, can be managed by each of the data domains. However, central data discovery, reporting, and auditing is needed to make it easy for users to find data, and for auditors to verify compliance.
- **Common access** – Data must be easily consumable by subject matter experts, such as data analysts and data scientists, and by purpose-built analytics and machine learning (ML) services, such as Amazon Athena, Amazon Redshift, and Amazon SageMaker. This requires data domains to expose a set of interfaces that make data consumable while enforcing appropriate access controls and audit tracking.

The following are user experience considerations:

- Data teams own their information lifecycle, from the application that creates the original data, to the analytics systems that extract and create business reports and predictions. Through this lifecycle, they own the data model, and determine which datasets are suitable for publication to consumers.
- Data domain producers expose datasets to the rest of the organization by registering them with a central catalog. They can choose what to share, for how long, and how consumers can interact with them. They're also responsible for maintaining the data and making sure it's accurate and current.
- Data domain consumers and individual users should be given access to data through a supported interface, such as a data API, that helps ensure consistent performance, tracking, and access controls.
- All data assets are easily discoverable from a single central data catalog. The data catalog contains the datasets registered by data domain producers, including supporting metadata, such as lineage, data quality metrics, ownership information, and business context.
- All actions taken with data, usage patterns, data transformations, and data classifications should be accessible through a single, central place. Data owners, administrators, and auditors should be able to inspect an organization's data compliance posture in a single place.

Let's start with a high-level reference design that builds on top of the data mesh pattern. It further separates consumers, producers, and central governance to highlight the key aspects discussed previously. However, note that a data domain, in a data mesh pattern, might represent a data consumer, a data producer, or both.

The AWS Lake House architecture relies on an AWS Glue and AWS Lake Formation Data Catalog for users to access the objects as tables. The users are entitled to these tables using Lake Formation, which is one per AWS account. Each Lake Formation account has its own Data Catalog, but storing the metadata on the data objects on multiple accounts across various catalogs makes it hard for the consumers to select the table. A consumer has to log into individual accounts to see the objects, assuming that the consumer knows exactly where to look. A central catalog also makes it easy to feed into a central business catalog and allows easier auditing of grants or revokes (it just makes it easier; it does not provide a single store of audits). Therefore, a central Data Catalog is recommended.

The metadata being on the central catalog does not make the tables in individual lakes accessible to all the consumers automatically. The actual entitlement on tables is individually granted and revoked by the application owner.

This allows the data mesh objective of the data strategy where the data is stored in multiple individually managed lakes, as opposed to a single central lake, while being accessible, provided properly entitled, to all the consumers. The role of the Data Catalog is of paramount importance here as the consumers can locate the proper storage of the data, they are interested in.

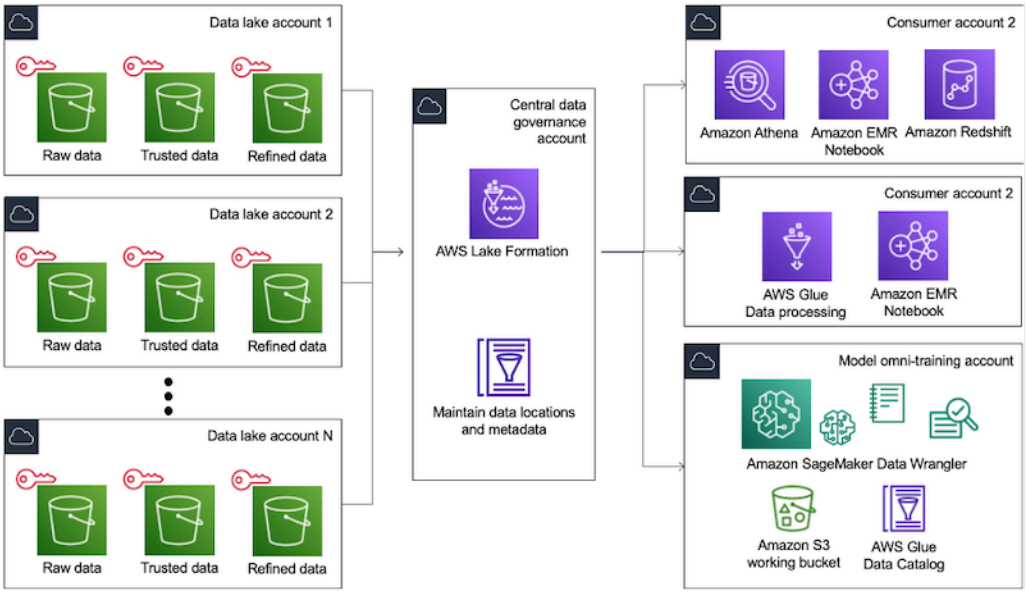
Term	Definition
Data mesh	Data is stored in multiple data stores, not in one single store. Consumers can access them as needed, assuming they are properly entitled.
AWS Lake Formation	A service that makes the data available as tables. Allows the owner of that table to give permissions to consumers.
AWS Glue Data Catalog (Data Catalog)	A data store containing metadata about the data, for example, table name, the columns in them, and user-defined tags. It does not contain actual data. This allows a consumer to know what to select.
Amazon Athena	A managed service that allows a user to enter a SQL query to select data. It in turn fetches the data and presents it in a tabular format. Athena needs a Data Catalog to let the consumer know the columns to select.
Resource link	A link that extends from one catalog to another and allows the consumers in the remote catalog to view and query the tables in the remote database as if the tables were in their local database. There are two types of resource links: for a specific table, and for an entire database.

Reference architecture

Here is a pattern for a single producer account, a single consumer account, and a central Lake Formation account. Each account has an AWS Glue Data Catalog. The central account's Data Catalog is considered the main catalog. Resource links are established to the producer and consumer accounts. This way, when the central account changes something, both accounts get the schema updates. The consumers selecting data will always see the most recent metadata.

The producer account always has the authority to grant or revoke the permissions on the tables in its Data Catalog. The central Lake Formation account is merely a holder of metadata, which sends it to all the consumer accounts which has a subscription via a resource link. Under no circumstances the central Lake Formation account can grant on its own.

With the concept in place, let’s look at three design patterns for deploying a data mesh architecture.



Data mesh reference architecture

Workflow from producer to consumer:

1. Data source locations hosted by the producer are created within the producer's AWS Glue Data Catalog and registered with Lake Formation.
2. When a dataset is presented as a product, producers create Lake Formation Data Catalog entities (database, table, columns, attributes) within the central governance account. This makes it easy to find and discover catalogs across consumers. However, this doesn't grant any permission rights to catalogs or data to all accounts or consumers, and all grants are be authorized by the producer.
3. The central Lake Formation Data Catalog shares the Data Catalog resources back to the producer account with required permissions via Lake Formation resource links to metadata databases and tables.
4. Lake Formation permissions are granted in the central account to producer role personas (such as the data engineer role) to manage schema changes and perform data transformations (alter, delete, update) on the central Data Catalog.
5. Producers accept the resource share from the central governance account so they can make changes to the schema at a later time.
6. Data changes made within the producer account are automatically propagated into the central governance copy of the catalog.
7. Based on a consumer access request, and the need to make data visible in the consumer's AWS Glue Data Catalog, the central account owner grants Lake Formation permissions to a consumer account based on direct entity sharing, or based on tag-based access controls, which can be used to administer access via controls like data classification, cost center, or environment.
8. Lake Formation in the consumer account can define access permissions on these datasets for local users to consume. Users in the consumer account, like data analysts and data scientists, can query data using their chosen tool such as Athena and Amazon Redshift.

In some cases, multiple catalogs are necessary and there is no other alternative. For example, if data is sent to both Regions, there will be two Data Catalogs that need to be maintained.

Option 1: Central data governance model

Here is a more practical model with multiple producers and consumers accounts. There is still a single central data governance account, which has resource links to all the other accounts. Note that we didn't

deliberately name them with specific lines of business (LOBs), since this model applies to any LOB and any number of lakes.

Roles of various accounts

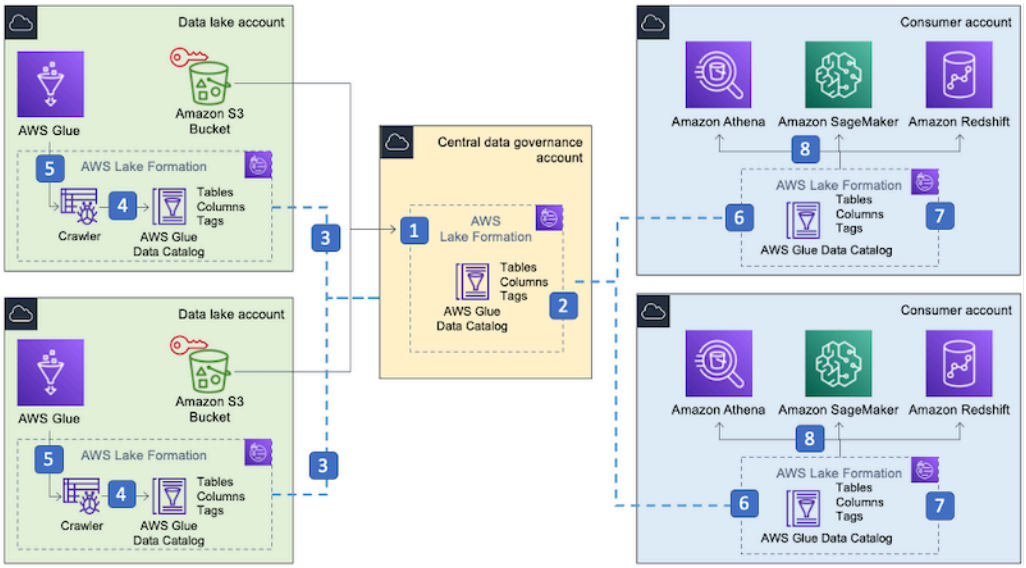
Here are the roles of the various types of accounts.

Account	Description
Producer account	• Allows data producers to write data into their respective S3 buckets. • Does not allow interactive access to S3 buckets or objects in them. • Allows only production ETL jobs to perform transformation, movement, etc.
Consumer account	• Allows data consumption through Athena, Redshift Spectrum, and web apps. • Only cataloged items can be queried, not all objects in the bucket. • Isolates the data changes (done by producer account) from data access (consumer accounts).
Central account	• This is a central catalog of all metadata. If additional consumer accounts are created, the metadata is replicated from this central account. • Since all metadata is in one place, it allows easier auditing of actions like grants and revokes on tables. The actual auditing is still decentralized but a central account makes the reporting easier. • Consumer accounts need to access the metadata using resource links to this central catalog only. • Does not contain any actual data. Only logs are stored here.

Notes

- These are just roles and they are not mutually exclusive. It's possible to have one AWS account with both roles of producer and consumer. A batch serving account is such an example.
- These accounts are Region-specific and are all in the same Region. They are not across Regions.

These accounts interact as shown in the following diagrams



Central data governance model

The producers can onboard their dataset table names, but the tables are completely independent and federated in central data governance account.

Advantages

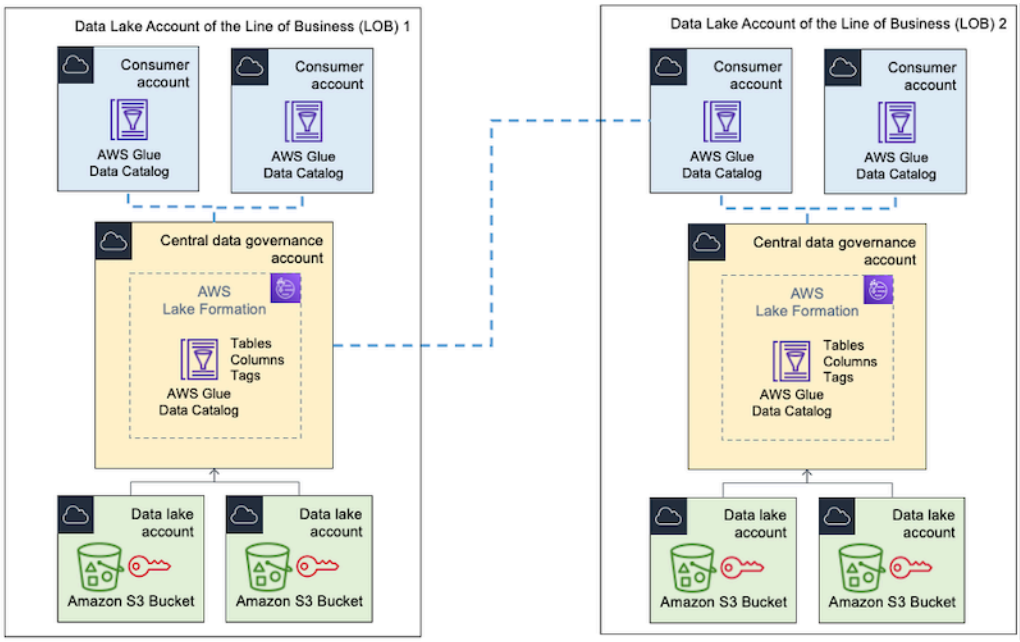
- All datasets are available in one place for querying.
- Entitlements become easier.
- A single database to database resource link is enough (assuming database-to-database resource links are allowed).
- Single source of data truth – one-way sharing of catalog across various organizations.
- The LOBs still have the choice to define metadata, schema evolution and manage permissions. The central Lake Formation account does not enforce anything on them.
- Allows centralized auditing.
- Allows local sandbox accounts for consumers, which is useful in cases such as model training and serving.

Disadvantages

- More complex for consumer analysts than using one data warehouse.
- Required skills are more aligned to security and governance than analytics.
- Technology solution – may not solve issues created by misaligned LOBs incentives.

Option 2: Federated Line of Business (LOB) central governance model

In this model, each LOB maintains an independent central Lake Formation account, which eases the use of centralized auditing in that LOB. Consumer accounts can see the data from producer accounts in the same LOB only. For accessing the data across LOBs, they need to establish the resource links to the appropriate catalog.



Federated LOB central governance model

Advantages

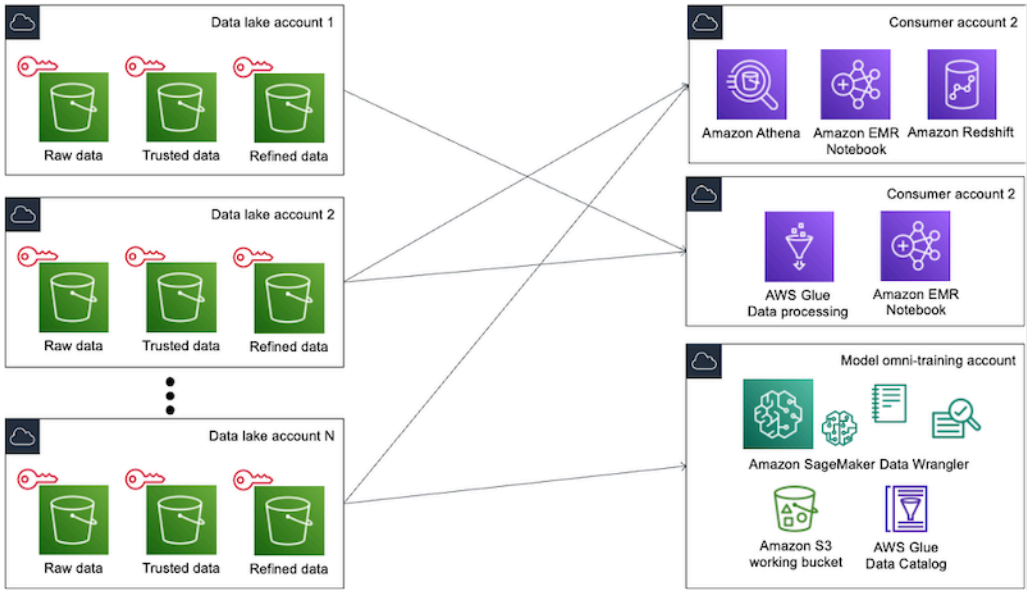
- Each LOB still maintains their own Lake Formation central account and access control.
- The blast radius in case of non–availability of a single Lake Formation account is reduced.

Disadvantages

- Centralized metadata is impossible since there is no central account. Audits from each central account need to be pulled and consolidated.
- Resource links need to be created across multiple catalogs. This makes it difficult to maintain the links, especially as the number of lakes grows.

Option 3: Completely federated data governance model

In this model, there is no central Lake Formation. Each producer account maintains their own Data Catalog and each consumer accesses the Data Catalog via a resource link.



Completely federated data governance model

Advantages

- There is complete separation among the Lake Formation accounts.
- Local queries go to the local Lake Formation Data Catalog. They don't need the trip to the central Lake Formation.
- Any operator error that deletes a single Lake Formation account will not affect anything else, even inside the same LOB.

Disadvantages

- Entitlements will need to be distributed.
- Multiple resource links need to be created and maintained, which quickly becomes a burden in the data organization scale.
- When data from a central business catalog is replicated over to the other Lake Formation catalogs, all those Lake Formation catalogs need to be updated individually.

Batch data processing

Most analytics applications require frequent batch processing, which allows them to process data in batches at varying interval. For example, processing daily sales aggregations by individual store and then writing that data to the data warehouse on a nightly basis can allow business intelligence (BI) reporting queries to run faster. Batch systems must be built to scale for all sizes of data and scale seamlessly to the size of the dataset being processed at various job runs.

It is important for the batch processing system to be able to support disparate source and target systems, process various data formats, seamlessly scale out to process peak data volumes, ability to orchestrate jobs using workflow, provide a simple way to monitor the jobs and most importantly offer an ease of use development framework that accelerates job development. Business requirements might dictate that batch data processing jobs be bound by an SLA, or have certain budget thresholds. Use these requirements to determine the characteristics of the batch processing architecture.

On AWS, analytic services, such as Amazon EMR , Amazon Redshift , Lake Formation Blueprints , and AWS Glue family services namely Glue ETL , Glue Workflows , AWS Glue DataBrew , AWS Glue Elastic

Views allow you to run batch data processing jobs at scale for all batch data processing use cases and for various personas, such as data engineer, data analyst, and data scientists. While there are some overlapping capabilities between these services, knowing the core competencies and when to use which service or services allow you to accomplish your objectives in the most effective way.

Characteristics

Following are the key characteristics that determine how you should plan when developing a batch processing architecture.

Ease of use development framework: This is one of the most important characteristics that truly allows personas of ETL developers and data engineers, data analysts, and data scientists to improve their overall efficiencies. An ETL developer benefits from a hybrid development interface that helps them to use the best of both—developing part of their job and switching to writing customized complex code where applicable. Data analysts and data scientists spend a lot of their time preparing data for actual analysis, or capturing feature engineering data for their machine learning models. You can improve their efficiencies in data preparation by adopting a no-code data preparation interface which helps them to normalize and clean data up to 80% faster compared to traditional approached to data preparation.

Support disparate source and target systems: Your batch processing system should have the ability to support various different types of data sources and targets between relational, semi-structured, non-relational, and SaaS providers. When operating in the cloud, a connector ecosystem can benefit you by seamlessly connecting to various sources and targets, and can simplify your job development.

Support various data file formats: Some of the commonly seen data formats are CSV, Excel, JSON, Apache Parquet, Apache ORC, XML, and Logstash Grok. Your job development can be accelerated and simplified if the batch processing services can natively profile these various file formats, infer schema automatically (including complex nested structures) so that you can focus more on building transformations.

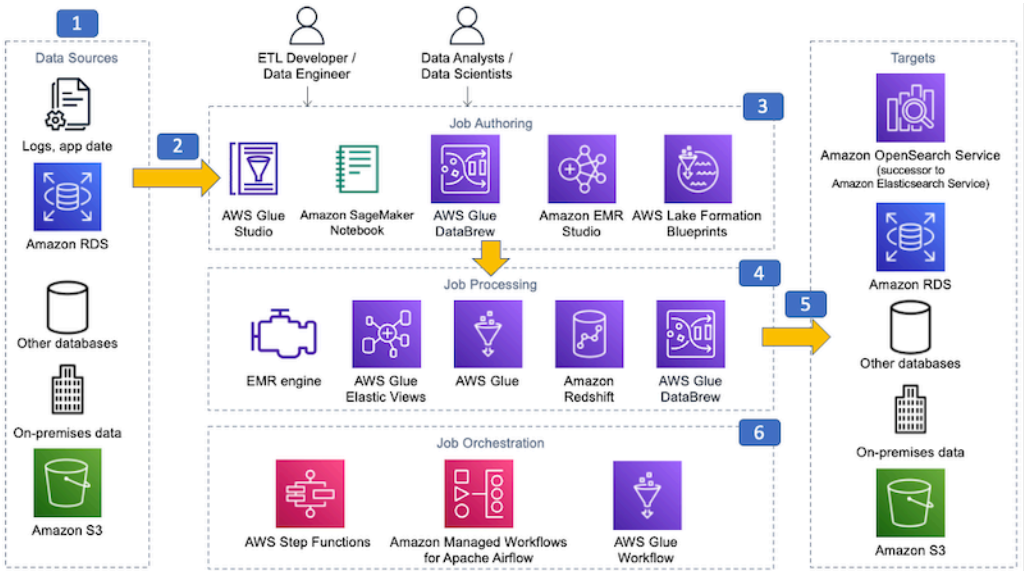
Seamlessly scale out to process peak data volumes: Most batch processing jobs experience varying data volumes. Your batch processing job should have the ability to scale out to handle peak data spikes and scale back in when the job completes.

Simplified job orchestration with job bookmarking capability: The ability to develop job orchestration with dependency management, and the ability to author the workflow using API, CLI, and a graphical user interface allows for a robust CI/CD integration.

Ability to monitor and alert on job failure: This is an important measure for ease of operational management. Having quick and easy access to job logs, and a graphical monitoring interface to access job metrics can quickly help you identify errors and tuning opportunities for your job. Coupling that with an event-driven approach to alert on job failure will be invaluable for easing operational management.

Provide a low-cost solution: Costs can quickly get out of control if you do not plan correctly. A pay as you go pricing model for both compute and authoring jobs can help you overcome hefty costs upfront and allows you to only pay for what you use instead of overpaying to accommodate for peak workloads. Use automatic scaling to accommodate spiky workloads when necessary. Using Spot Instances where applicable can bring your costs down for workloads where they are a good fit.

Reference architecture



Batch data processing reference architecture

1. Batch data processing systems typically require a persistent data store for source data. When developing batch data processing applications on AWS, you can use data from various sources, including your on-premises data stores, Amazon RDS, Amazon S3, DynamoDB, and any other databases that are accessible from the cloud.
2. Data processing jobs need access to a variety of data stores to read data. You can use AWS Glue connectors from the AWS Marketplace to connect to a variety of data stores, such as Google BigQuery, and SAP HANA. You can also connect to SaaS application providers, such as Salesforce, ServiceNow, and Google Analytics, using AWS Glue DataBrew and Amazon AppFlow. In addition, you can always rely on the custom JDBC capability in Apache Spark and connect to any JDBC-compliant data store from Amazon EMR or AWS Glue jobs.
3. Choosing the right authoring tool for the job simplifies job development and improves agility.
    a. You can use AWS Glue Studio when authoring jobs for the AWS Glue Spark runtime engine.
    b. Use AWS Glue Blueprints when you need to create a self-service parametrized job for analysts and control what data the analyst is allowed to access.
    c. Use Amazon EMR notebook for interactive job development and scheduling notebook jobs against Amazon EMR.
    d. Use Amazon SageMaker Notebook when working within SageMaker ML development.
    e. Use AWS Glue DataBrew from the AWS Management Console or from a Jupyter Notebook for no-code development experience.
    f. Use Lake Formation Blueprints when you need to quickly create batch data ingestion jobs to rapidly build a data lake in AWS.
4. Choosing the right processing engine for your batch jobs allows you to be flexible with managing costs and lowering operational overhead. Today, only Amazon EMR and Amazon Redshift offer the ability to autoscale seamlessly based on your job runtime metrics using the managed scaling feature and concurrency scaling features for read and write (preview) respectively. Other services depicted under job processing in the reference architecture require you to specify the maximum processing capacity for your job, which will be used to accommodate peak data volumes. Amazon EMR and Amazon Redshift offer server-based architectures while rest of the services depicted in the reference architecture are fully serverless. Amazon EMR allows you to use Spot Instances for suitable workloads that can further save your costs. A good strategy is to complement these processing engines to meet the business objectives of the SLA, functionality, and lower TCO by choosing the right engine for the right job.

5. Batch processing jobs usually require writing processed data to a target persistent store. This store can reside anywhere between AWS, on-premises, or other cloud providers. You can use the rich connector interface AWS Glue offers to write data to various target platforms, such as Amazon S3, Snowflake, and Amazon OpenSearch Service. You can also use the native spark JDBC connector feature and write data to any supported JDBC target.
6. All batch jobs require a workflow that can handle dependency checks to ensure no downstream impacts and have a bookmarking capability that allows them to resume where they left off in the event of a failure or at the next run of the job. When using AWS Glue as your batch job processing engine, you can use the native workflow capability to help you create a workflow with a built-in state machine to track the state of your job across the entire workflow. Glue jobs also support a bookmarking capability that keeps track of what it has processed and what needs to be processed during next run. Similarly, AWS Lake Formation blueprints support a bookmarking capability when processing incremental data. With EMR Studio, you can schedule notebook jobs. When using any of the analytic processing engines, you can build job workflows using an external scheduler, such as AWS Step Functions or Amazon Managed Workflows for Apache Airflow that allows you to interoperate between any service including external dependencies.
7. Batch processing jobs write data output to target data store, which can be anywhere within the AWS Cloud, on premises, or at another cloud provider. You can use the AWS Glue Data Catalog to crawl the supported target databases to simplify writing to your target database.

Configuration notes

Use AWS Glue Data Catalog as a central metastore for your batch processing jobs, regardless of which AWS analytic service you use as a processing engine. Batch processing jobs cater to a variety of workloads ranging from running several times an hour or day, to running monthly or quarterly The data volumes vary significantly and so do the consumption patterns on the processed dataset. Always work backwards to understand the business SLAs and develop your job accordingly. The central Data Catalog makes it easy for you to use the right analytic service to meet your business SLAs and other objectives, thereby creating a central analytic ecosystem.

Avoid lifting and shifting server-based batch processing systems to AWS. By lifting and shifting traditional batch processing systems into AWS, you risk running over-provisioned resources on Amazon EC2. For example, traditional Hadoop clusters are often over-provisioned and idle in an on-premises setting. Use AWS Managed Services, such as AWS Glue, Amazon EMR, and Amazon Redshift, to simplify your architecture using a lake house pattern and remove the undifferentiated heavy lifting of managing clustered and distributed environments.

Automate and orchestrate everywhere. In a traditional batch data processing environment, it's a best practice to automate and schedule your jobs in the system. In AWS, you should use automation and orchestration for your batch data processing jobs in conjunction with the AWS APIs to spin up and tear down entire compute environments, so that you are only charged when the compute services are in use. For example, when a job is scheduled, a workflow service, such as AWS Step Functions, would use the AWS SDK to provision a new EMR cluster, submit the work, and shut down the cluster after the job is complete. Similarly, you can use Terraform or a CloudFormation template to achieve similar functionality.

Use Spot Instances and Graviton-based instance types on EMR to save costs and get better price performance ratio . Use Spot Instances when you have flexible SLAs that are resilient to job reruns upon failure and when there is a need to process very large volumes of data. Use Spot Fleet, EC2 Fleet, and Spot Instance features in Amazon EMR to manage Spot Instances.

Continually monitor and improve batch processing jobs. Batch processing systems evolve rapidly as data source volumes increase, new batch processing jobs are authored, and new batch processing frameworks are launched. Instrument your jobs with metrics, timeouts, and alarms to have the metrics and insight to make informed decisions on batch data processing system changes.

Streaming ingest and stream processing

Processing real-time streaming data requires throughput scalability, reliability, high availability, and low latency to support a variety of applications and workloads. Some examples include: streaming ETL, real-time analytics, fraud detection, API microservices integration, fraud detection activity tracking, real-time inventory and recommendations, and click-stream, log file, and IoT device analysis.

Streaming data architectures are built on five core constructs: data sources, stream ingestion, stream storage, stream processing, and destinations. Each of these components can be created and launched using AWS Managed Services and deployed and managed as a purpose-built solution on Amazon EC2, Amazon Elastic Container Service (Amazon ECS), or Amazon Elastic Kubernetes Service (Amazon EKS).

Examples of each of these components include:

Data sources: Application and click stream logs, mobile apps, existing transactional relational and NoSQL databases, IoT sensors, and metering devices.

Stream ingestion and producers: Both open source and proprietary toolkits, libraries, and SDKs for Kinesis Data Streams and Apache Kafka to create custom stream producers, AWS service integrations such as AWS IoT Core, CloudWatch Logs and Events, Amazon Kinesis Data Firehose, AWS Data Migration Service (DMS), and third-party integrations.

Stream storage: Kinesis Data Streams, Amazon Managed Streaming for Apache Kafka (Amazon MSK), and Apache Kafka.

Stream processing and consumers: Amazon EMR (Spark Structured Streaming, Apache Flink), AWS Glue ETL Streaming, Kinesis Data Analytics for Apache Flink, third-party integrations, and build-your-own custom applications using AWS and open source community SDKs and libraries.

Downstream destinations: Databases, data warehouses, purpose-built systems such as OpenSearch services, data lakes, and various third-party integrations.

With these five components in mind, next let's consider the characteristics as you design your stream processing pipeline for real-time ingestion and nearly continuous stream processing.

Characteristics

Scalable throughput: For real-time analytics, you should plan a resilient stream storage infrastructure that can adapt to changes in the rate of data flowing through the stream. Scaling is typically performed by an administrative application that monitors shard and partition data-handling metrics.

Dynamic stream processor consumption and collaboration: Stream processors and consumers should automatically discover newly added Kinesis shards or Kafka partitions, and distribute them equitably across all available resources to process independently or collaboratively as a consumption group (Kinesis Application Name, Kafka Consumer Group).

Durable: Real-time streaming systems should provide high availability and data durability. For example, Amazon Kinesis Data Streams and Amazon Managed Streaming for Apache Kafka replicate data across Availability Zones providing the high durability that streaming applications need.

Replay-ability: Stream storage systems should provide the ordering of records within shards and partitions, as well as the ability to independently read or replay records in the same order to stream processors and consumers.

Fault-tolerance, checkpoint, and replay: Checkpointing refers to recording the farthest point in the stream that data records have been consumed and processed. If the consuming application crashes, it can resume reading the stream from that point instead of having to start at the beginning.

Loosely coupled integration: Loosely coupled integration: A key benefit of streaming applications is the construct of loose coupling. The value of loose coupling is the ability of stream ingestion, stream

producers, stream processors, and stream consumers to act and behave independently of one another. Examples include the ability to scale consumers outside of the producer configuration and adding additional stream processors and consumers to receive from the same stream or topic as existing stream processors and consumers, but perform different actions.

Allow multiple processing applications in parallel: The ability for multiple applications to consume the same stream concurrently is an essential characteristic of a stream processing system. For example, you might have one application that updates a real-time dashboard and another that archives data to Amazon Redshift. You want both applications to consume data from the same stream concurrently and independently.

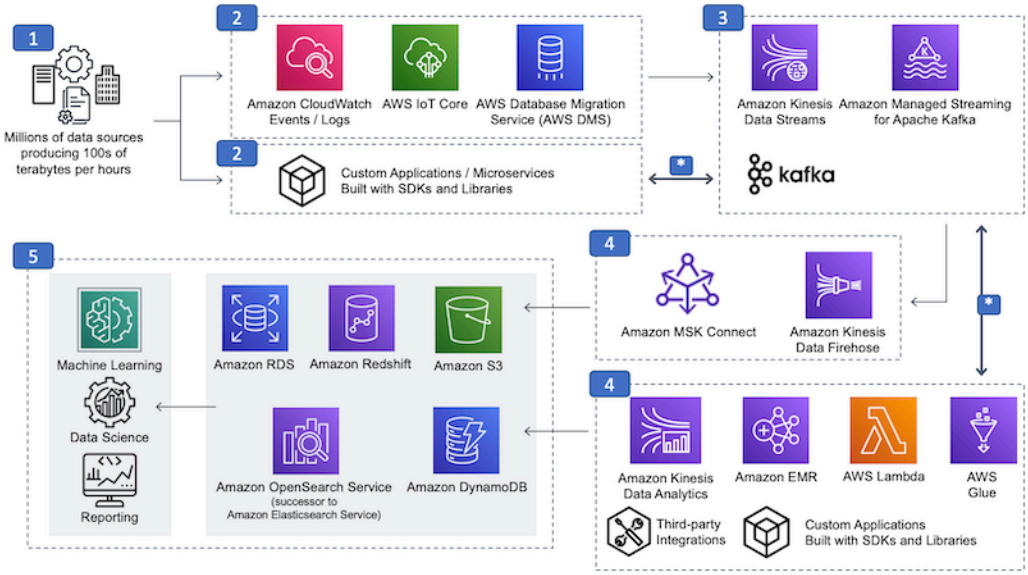
Messaging semantics: In a distributed messaging system, components might fail independently. Different messaging systems implement different semantic guarantees between a producer and a consumer in the case of such a failure. The most common message delivery guarantees implemented are:

- **At most once**: Messages that could not be delivered, or are lost, are never redelivered
- **At least once**: Message might be delivered more than once to the consumer
- **Exactly once**: Message is delivered exactly once

Depending on your application needs, you need to choose a message delivery system that supports one or more of these required semantics.

Security: Streaming ingest and processing systems need to be secure by default. You need to grant access by using the principal of least privilege to the streaming APIs and infrastructure, and encrypt data at rest and in transit. Both Kinesis Data Streams and Amazon MSK can be configured to use AWS IAM policies to grant least privilege access. For stream storage in particular, allow encryption in transit for producers and consumers, and encryption at rest.

Reference architecture



Streaming data analytics reference architecture

The preceding streaming reference architecture diagram is segmented into the previously described components of streaming scenarios:

1. Data sources
2. Stream ingestion and producers

3. Stream storage
4. Stream processing and consumers
5. Downstream destinations

All, or portions, of this reference architecture can be used for workloads such as application modernization with microservices, streaming ETL, ingest, real-time inventory, recommendations, or fraud detection.

In this section, we will identify each layer of components shown in the preceding diagram with specific examples. The examples are not intended to be an exhaustive list, but rather an attempt to describe some of the more popular options.

The subsequent Configuration notes section provides recommendations and considerations when implementing streaming data scenarios.

Note : There are two bidirectional event flow lanes noted with an asterisk (*) in the diagram. We will review the five core components of streaming architecture first, and then discuss these specialized flows.

- **Data sources** : The number of potential data sources is in the millions. Examples include application logs, mobile apps and applications with REST APIs, IoT sensors, existing application databases (RDBMS, NoSQL) and metering records.
- **Stream ingestion and producers** : Multiple data sources generate data continually that might amount to terabytes of data per day. Toolkits, libraries, and SDKs can be used to develop custom stream producers to streaming storage. In contrast to custom developed producers, examples of pre-built producers include Kinesis Agent, Change Data Capture (CDC) solutions, and Kafka Connect Source connectors.
- **Streaming storage** : Kinesis Data Streams, Managed Streaming for Apache Kafka, and self-managed Apache Kafka are all examples of stream storage options for ingesting, processing, and storing large streams of data records and events. Streaming storage implementations are modeled on the idea of a distributed, immutable commit log. Events are stored for a configurable duration (hours to days to months, or even permanently in some cases). While stored, events are available to any client.
- **Stream processing and consumers** : Real-time data streams can be processed sequentially and incrementally on a record-by-record basis over sliding time windows using a variety of services. Or, put another way, this can be where particular domain-specific logic resides and is computed.

With Kinesis Data Analytics for Apache Flink or Kinesis Data Analytics Studio, you can process and analyze streaming data using standard SQL in a serverless way. The service allows you to quickly author and run SQL queries against streaming sources to perform time series analytics, feed real-time dashboards, and create real-time metrics.

If you work in an Amazon EMR environment, you can process streaming data using multiple options—Apache Flink or Spark Structured Streaming.

Finally, there are options for AWS Lambda, third-party integrations, and build-your-own custom applications using AWS SDKs, libraries, and open-source libraries and connectors for consuming from Kinesis Data Streams, Managed Streaming for Apache Kafka, and Apache Kafka.

- **Downstream destinations** : Data can be persisted to durable storage to serve a variety of use cases including ad hoc analytics and search, machine learning, alerts, data science experiments, and additional custom actions.

A special note on the data flow lanes noted with asterisk (*). There are two examples which both involve bidirectional flow of data to and from layer #3 streaming storage.

The first example is the bidirectional flow of in-stream ETL between stream processor (#4) which uses one or more raw event sources from stream storage (#3) and performs, filtering, aggregations, joins,

etc. and writes results back to streaming storage to a refined (that is, curated, hydrated) result stream or topic (#3) where it can be used by a different stream processor or downstream consumer.

The second bidirectional flow example is the ubiquitous application modernization microservice design (#2) which often use a streaming storage layer (#3) for decoupled microservice interaction.

The key takeaway here is for us to not presume that the streaming event flows exclusively from left-to-right over time in the reference architecture diagram.

Configuration notes

As explored so far, we know streaming data architects have options for implementing particular components in their stack, for example, different options for streaming storage, streaming ingest, and streaming producers. While it's impractical to provide in-depth recommendations for each layer's options in this document, there are some high-level concepts to consider as guide posts, which we will present next.

For more in-depth analysis of a particular layer in your design, consider exploring the provided links within the following guidelines.

Streaming application guidelines

Determine business requirements first. It's always a best practice and practical to focus on your workload's particular needs first, rather than starting with a feature-by-feature comparison between the technical options. For example, we often see organizations prioritizing Technical Feature A vs. Technical Feature B before determining their workload's requirements. This is the wrong order. Determine your workload's requirements first because AWS has a wide variety of purpose-built options at each streaming architecture layer to best match your requirements.

Technical comparisons second. After business requirements have been clearly established, the next step is to match your business requirements with the technical options that offer the best chance for success. For example, if your team has few technical operators, serverless might be a good option. Other technical questions about your workload might be whether you require a large number of independent stream processors and consuming applications, that is, one vs. many stream processors and consumers. What kind of manual or automatic scaling options are available to match business requirement throughput, latency, SLA, RPO, and RTO objectives? Is there a desire to use open source-based solutions? What are the security options and how well do they integrate into existing security postures? Is one path easier or more straightforward to migrate to versus another, for example, self-managed Apache Kafka to Amazon MSK. To learn more about your options for various layers in the reference architecture stack, refer to the following:

- **Streaming ingest and producers** — Can be workload-dependent and use AWS service integrations, such as AWS IoT Core, CloudWatch Logs and Events, AWS Data Migration Service (AWS DMS), and third-party integrations (Refer to: Writing Data to Amazon Kinesis Data Streams in Amazon Kinesis Data Streams Developer Guide).
- **Streaming storage** — Kinesis Data Streams, Kinesis Data Firehose, Amazon Managed Streaming for Apache Kafka (Amazon MSK), and Apache Kafka (Refer to: Best Practices in Amazon Managed Streaming for Apache Kafka Developer Guide).
- **Stream processing and consumers** — Kinesis Data Analytics for Apache Flink, Kinesis Data Firehose, AWS Lambda, open source and proprietary SDKs (Refer to: Advanced Topics for Amazon Kinesis Data Streams Consumers in Amazon Kinesis Data Streams Developer Guide and Best Practices for Kinesis Data Analytics for Apache Flink in Amazon Kinesis Data Analytics Developer Guide).

Remember separation of concerns. Separation of concerns is the application design principle that promotes segmenting an application into distinct, particular area of concerns. For instance, your application might require that stream processors and consumers are performing an aggregation computation in addition to recording the computation results to a downstream destination. While

it can be tempting to clump both of these concerns into one stream processors or consumers, it is recommended to consider separation instead. It's often better in the segment isolate into multiple stream processors or consumers for operation monitoring, performance tuning isolation, and reducing the downtime blast radius.

Development

Existing or desired skills match. Realizing value from streaming architectures can be difficult and often a new endeavor for various roles within organizations. Increase your chances of success by aligning your team's existing skillsets, or desired skillsets, wherever possible. For example, is your team familiar with Java or do they prefer a different language, such as Python or Go? Does your team prefer a graphical user interface for writing and deploying code? Work backwards from your existing skill resources and preferences to appropriate options for each component.

Build vs. buy (Write your own or use off-the-shelf). Consider whether an integration between components already exists or if you need to write your own. Or perhaps both options are available. Many teams new to streaming incorrectly assume that everything needs to be written from scratch. Instead, consider services such as Kafka Connect Connectors for inbound and outbound traffic, AWS Lambda, and Kinesis Data Firehose.

Performance

Aggregate records before sending to stream storage for increased throughput. When using Kinesis, Amazon MSK, or Kafka, ensure that the messages are accumulated on the producer side before sending to stream dtorage. This is also referred to as batching records to increase throughput, but at the cost of increased latency.

When working with Kinesis Data Streams, use Kinesis Client Library (KCL) to de-aggregate records. KCL takes care of many of the complex tasks associated with distributed computing, such as load balancing across multiple instances, responding to instance failures, checkpointing processed records, and reacting to re-sharding.

Initial planning and adjustment of shards and partitions. The most common mechanism to scale stream storage for stream processors and consumers is through the number of configured shards (Kinesis Data Streams) or partitions (Apache Kafka, Amazon MSK) for a particular stream. This is a common element across Kinesis Data Streams, Amazon MSK, and Apache Kafka, but options for scaling out (and in) the number of shards or partitions vary.

- Amazon Kinesis Data Streams Developer Guide: Resharding a Stream
- Apache Kafka Documentation - Operations: Expanding your cluster (also applicable to Amazon MSK)
- Amazon Managed Streaming for Apache Kafka Developer Guide: Using LinkedIn's Cruise Control for Apache Kafka with Amazon MSK (for partition rebalancing)

Use Spot Instances and automatic scaling to process streaming data cost effectively. You can also process the data using AWS Lambda with Kinesis, Amazon MSK, or both, and Kinesis record aggregation and deaggregation modules for AWS Lambda . Various AWS services offer automatic scaling options to keep costs lower than provisioning for peak volumes.

Operations

Monitor Kinesis Data Streams and Amazon MSK metrics using Amazon CloudWatch . You can get basic stream and topic level metrics in addition to shard and partition level metrics. Amazon MSK also provides an Open Monitoring with Prometheus option.

1. Amazon Kinesis Data Streams Developer Guide: Monitoring Amazon Kinesis Data Streams
2. Amazon Managed Streaming for Apache Kafka Developer Guide: Monitoring an Amazon MSK Cluster

Plan for the unexpected / No single point of failure. Some components in your streaming architecture will offer different options for durability in case of a failure. Kinesis Data Streams replicates to three different Availability Zones. With Apache Kafka and Amazon Managed Streaming for Apache Kafka (Amazon MSK), for example, producers can be configured to require acknowledgement for partition leader as well as a configurable amount in-sync replica followers before considering the write successful. In this example, you are able to plan for possible disruptions in your AWS environment, for example, if an Availability Zone goes offline, without possible downtime of your producing and consuming layers.

Security

Authentication and authorization.

- Amazon Managed Streaming for Apache Kafka Developer Guide: Authentication and Authorization for Apache Kafka APIs
- Amazon Kinesis Data Streams Developer Guide: Controlling Access to Amazon Kinesis Data Streams Resources Using IAM

Encryption in transit, encryption at rest. Streaming data actively moves from one layer to another, such as from a streaming data producer to stream storage over the internet or through a private network. Protecting data in transit, enterprises can and often choose to use encrypted connections (HTTPS, SSL, TLS) to protect the contents of data in transit. Many AWS streaming services offer protection of data at rest through encryption.

- AWS Well-Architected Framework Security Pillar: Identity and Access Management
- AWS Lake Formation Developer Guide: Security in AWS Lake Formation
- Amazon Managed Streaming for Apache Kafka Developer Guide: Authentication and Authorization for Apache Kafka APIs
- Amazon Kinesis Data Streams Developer Guide: Controlling Access to Amazon Kinesis Data Streams Resources Using IAM

Operational analytics

Operational analytics refers to inter-disciplinary techniques and methodologies that aim to improve day-to-day business performance in terms of increasing efficiency of internal business processes and improving customer experience and value. Business analysts used the traditional analytics systems to recognize the business trends and identify the decisions. But by using the operational analytics systems, they can initiate such business actions based on the recommendations that the systems provide. They can also automate the execution processes to reduce the human errors. This makes the system go beyond being descriptive to being more prescriptive and even being predictive in nature.

Enterprises often have diverse and complex IT infrastructure. Challenges arise when trying to identify sources to extract from or identify what operational data captures the state of an analytics application. Traditionally this data came from logging information emanating from different parts of the system. Modern environments include trace and metric data along with log data. Trace data captures the user request for resources as it passes through different systems all the way to the destination and the response back to the user. Metric data contain various measurements that provide insight into the health or operational state of these systems. The combination of these form a rich set of diverse operational data that analytics application can be built on.

Characteristics

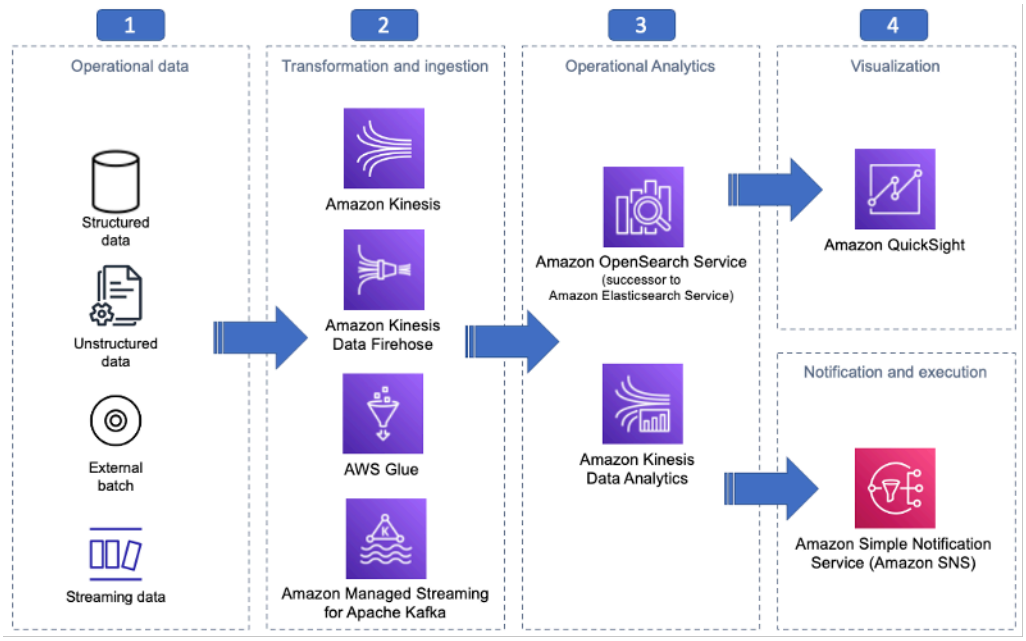
Discoverability: The ability of the system to make operational data available for consumption. This involves discovering multiple disparate types of data available within an application that can be used for various ad hoc explorations.

Observability: The ability to understand internal state from the various signal outputs in the system. By providing a holistic view of these various signals along with a meaningful inference it becomes easy understand how healthy and well performant the overall system is.

User centricity: Each analytics application should address a well-defined operational scope and solve a particular problem at hand. Users of the system often won't understand or care about the analytics process but only see the value the result.

Agility: The system must be flexible enough to accommodate changing needs of an analytics application and offer necessary control to bring in additional data with low overhead.

Reference architecture



Operational analytics reference architecture

Operational data: Operational data originates from various points in the environment and systems. It consists of log data including systems logs, machine logs, applications logs, events logs, audit and other logs; metric data systems metrics, resource utilization metrics, application performance metrics; trace data including request-response profile and other telemetric data.

Transformation and ingestion: This represents a layer that collects the operational data and performs additional dissection or enrichment or other transformation before being ingested into Amazon OpenSearch Service. These include decoration data from additional sources or transforming the data into form required for indexing.

Indexing: OpenSearch Service performs indexing of incoming transformed data and makes it available for near-real time searching.

Visualization: This layer brings in all the operational data present in the system into a single pane of glass in the forms of graphs, visualization, and other dashboards for the particular analytics application.

Downstream application: OpenSearch Service also allows operational data indexed to be available for machine learning, alerting, and reporting application.

Configuration notes

Choose data model before ingestion: When bringing data in from disparate sources, especially from structured systems into structureless systems such as OpenSearch, special care must be taken to ensure that the chosen data model provides a frictionless search experience for users.

Decide what data fields will be searchable: By default, Amazon OpenSearch Service indexes all data fields. This might not be desirable in situations like fully or partially matching on numeric data types.

Use tiered storage: The value of operational data or any timestamped data generally decreases with the age of the data. Moving aged data into tiered storage can save significant operational cost. Summarized rollups that can condense the data also can help address storage cost.

Monitor all involved components: Monitor all involved components with metrics in Amazon CloudWatch.

Data visualization

Every day, the people in your organization make decisions that affect your business. When they have the right information at the right time, they can make the choices that move your company in the right direction. Giving the decision-makers the opportunity to explore and interpret information in an interactive visual environment helps democratize data and accelerates data-driven insights that are easy to understand and navigate.

Building a BI and data visualization service in the cloud allows you to take advantage of capabilities such as scalability, availability, redundancy, and enterprise grade security. It also lowers the barrier to data connectivity and allows access to far wider range of data sources —both traditional, such as databases, as well as non-traditional, such as SaaS sources. An added advantage of a cloud-based data visualization service is the elimination of undifferentiated heavy lifting related to managing server infrastructure.

Characteristics

Scalability: Ensure that the underlying BI infrastructure is able to scale up vertically and horizontally both in terms of concurrent users as well as data volume. For example on AES, Amazon QuickSight SPICE and web application automatically scales up server capacity to accommodate a large number of concurrent users without any manual intervention in terms of provisioning additional capacity for data, for load balance, and others.

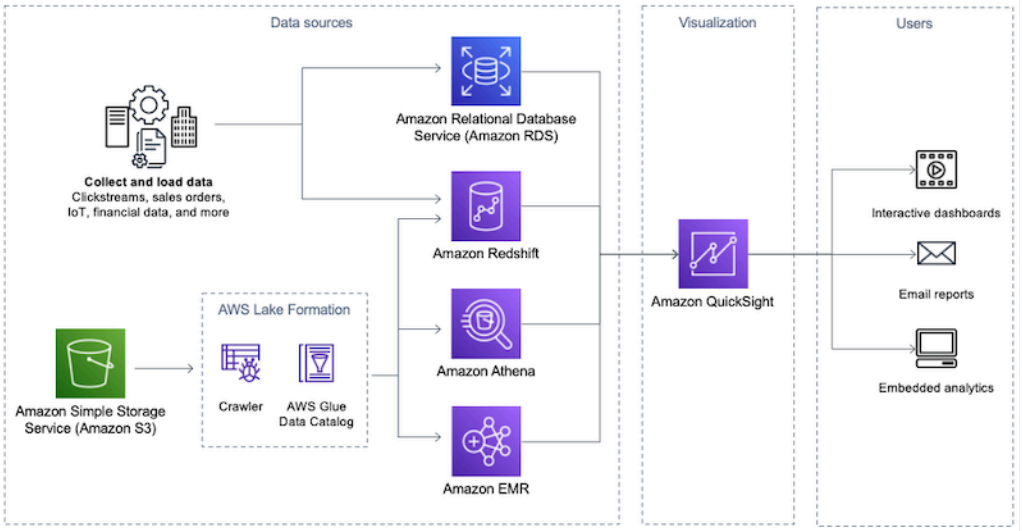
Connectivity: BI applications must be able to not just connect with data platforms like traditional Data Warehouse and databases but also support connectivity to data lake and lake house architectures. The application must also have the capacity to connect to non-traditional sources such as SaaS applications. Typically, data stores are secured behind a private subnet and BI tools and applications must be able to connect in a secure mechanism using strategies, such as VPC endpoints and secure firewalls.

Centralized security and compliance: BI applications must allow for a layered approach for security. This includes: Securing at the perimeter using techniques such as IP allow lists, security groups, ENIs and IAM policies for cloud resource access, securing the data in transit and data at rest using SSL and encryption, and restricting varying levels of access through fine-grained permissions for users to the underlying data and BI assets. The application must also comply with the governmental and industry regulations for the country or region the company is bound by.

Sharing and collaboration: BI applications must support data democratization. They must have features that allow sharing of the dashboards with other users in the company as well as for multiple report authors to collaborate with one another by sharing access to the underlying dataset. Not all BI tools have this capability. Amazon QuickSight allows the sharing of assets, such as DataSources, DataSets, Analyses, Dashboards, Themes, and Templates.

Logging, monitoring, and auditing: BI applications must provide adequate mechanisms to monitor and audit the usage of the application for security (to prevent unwanted access to data assets and other resources) and troubleshooting. Amazon QuickSight can be used with Amazon CloudWatch, AWS CloudTrail, and IAM to track record of actions taken by a user, user role, or an AWS service. This provides the who, what, when, and where of every user action in QuickSight.

Reference architecture



QuickSight dashboard end-to-end design

Data sources: Supports connection with traditional Data Warehouse or databases and also have the capacity to connect to non-traditional sources such as SaaS applications. Supported datasources in QuickSight include Amazon S3, Amazon Redshift, Amazon Aurora, Oracle, MySQL, Microsoft SQL Server, Snowflake, Teradata, Jira, ServiceNow and many more. Check here for the complete list of data sources supported in QuickSight. These data sources could be secured behind a private subnet and QuickSight can connect in a secure mechanism using strategies such as VPC Endpoints, Secure Firewalls and others.

Visualization Tool: Amazon QuickSight.

Consumers: Visual dashboard consumers accessing QuickSight console or embedded QuickSight analytics dashboard.

Configuration notes

Security: Implement the principle of least privilege throughout the visualization application stack. Ensure data sources are connected using VPC and restricting security groups to only required protocols, sources and destinations. Enforce that the users as well as applications in every layer of the stack are given just the right level of access permissions to data and the underlying resources. Ensure seamless integration with identity providers either industry supported or customized. In the case of multi-tenancy, use namespaces for better isolation of principals and other assets across tenants. For example, QuickSight follows the least privilege principle and access to AWS resources such as Amazon Redshift, Amazon S3 or Athena (common services used in data warehouse, data lake or lake House Architectures) can be managed through the QuickSight user interface. Additional security at the user or group level is supported using fine-grained access control through a combination of IAM permissions. Additionally, QuickSight features, such as row level security, column level security, and a range of asset governance capabilities that can be configured directly through QuickSight user interface.

Cost optimization: Accurately identify the volume of dashboard consumers and embedding requirements to determine the optimal pricing model for the given visualization use case. QuickSight

offers two different pricing options (capacity and user based), which allows clients to implement cost-effective BI solutions. Capacity pricing allows large-scale implementations and user-based pricing allows clients to get started with minimal investment (Note: SPICE has a 250M records or 500 GB volume per dataset limitation).

Low latency considerations: Use in-memory caching option, such as Memcached, Redis. or the in-memory caching engine in QuickSight called SPICE (Super-fast, Parallel, In-memory Calculation Engine) to prevent latency in dashboard rendering while accommodating any built-in restrictions that the Caching technology might have.

Pre-process data views: Ensure that the data is cleansed, standardized, enhanced, and pre-processed to allow analysis within the BI layer. If possible, create pre-processed, pre-combined, pre-aggregated data views for analysis purposes. ETL tools, such as Glue DataBrew, or techniques, such as materialized views, can be employed to achieve this.

Conclusion

This lens provides architectural guidance for designing and building reliable, secure, efficient, and cost-effective analytics workloads in the cloud. We captured common architectures and overarching analytics design tenets. The document also discussed the Well-Architected pillars through the Analytics Lens, providing you with a set of questions to consider for new or existing analytics architectures. Applying the framework to your architecture helps you build robust, stable, and efficient systems, leaving you to focus on running analytics workloads and pushing the boundaries of the field to which you're committed. The analytics landscape is continuing to evolve as the number of tools and processes grows and matures. As this evolution occurs, we will continue to update this paper to help you ensure that your analytics applications are well-architected.

Contributors

The following individuals and organizations contributed to this document:

- Wallace Printz: Senior SA, Amazon Web Services
- Radhika Ravirala: Principal SA, Amazon Web Services
- Indira Balakrishnan: Senior Specialist SA, Amazon Web Services
- Juan Yu: Senior Specialist SA, Amazon Web Services
- Richard Mei: Senior SA, Amazon Web Services
- Shankar Nivas: Principal Data Architect, Amazon Web Services
- Todd McGrath: Senior Specialist SA, Amazon Web Services
- Padmaja Suren: Senior Specialist SA, Amazon Web Services
- Harsha Tadiparthi: Principal Specialist SA, Amazon Web Services
- Muthu Pitchaimani: Analytics Specialist SA, Amazon Web Services
- Jongnam Lee: Senior Lead SA of AWS Well-Architected Data Analytics Lens, Amazon Web Services
- David Tucker: Senior Manager of Analytics SA, Amazon Web Services
- Srikanth Baheti: Senior Amazon QuickSight SSA, Amazon Web Services
- Raji Sivasubramaniam: Amazon QuickSight SSA, Amazon Web Services
- Ben Potter: Lead SA of AWS Well-Architected Security Pillar Amazon Web Services

Document history

To be notified about updates to this whitepaper, subscribe to the RSS feed.

Change	Description	Date
Minor update (p. 64)	Updates throughout and added placeholder for Sustainability.	September 14, 2022
Whitepaper updated (p. 7)	Corrected table of best practices in Design Principle 3.	December 16, 2021
Whitepaper updated (p. 64)	Title changed to Data Analytics Lens. Major updates applied throughout.	October 29, 2021
Initial publication (p. 64)	Analytics Lens first published.	May 20, 2020

Design principles arranged by pillar

These are the design principles outlined in this paper organized by pillar of the AWS Well-Architected Framework.

Operational excellence (p. 3)

- 1 - Monitor the health of the analytics pipelines (p. 3)
- 2 - Modernize deployment of the analytics jobs and applications (p. 5)
- 3 – Build financial accountability models for data and workload usage (p. 7)

Security (p. 9)

- 4 - Classify and protect data (p. 9)
- 5 - Control the data access (p. 13)
- 6 – Control the access to workload infrastructure (p. 17)

Reliability (p. 19)

- 7 - Design resiliency for analytics workload (p. 19)
- 8 - Govern data and metadata changes (p. 23)

Performance efficiency (p. 24)

- 9 - Choose the best-performing compute solution (p. 24)
- 10 - Choose the best-performing storage solution (p. 27)
- 11 - Choose the best-performing file format and partitioning (p. 28)

Cost optimization (p. 30)

- 12 - Choose cost-effective compute and storage solutions based on workload usage patterns (p. 31)
- 13 - Manage cost over time (p. 33)
- 14 - Use optimal pricing models based on infrastructure usage patterns (p. 36)

Notices

AWS glossary

For the latest AWS terminology, see the AWS glossary in the *AWS General Reference*.