AWS Well-Architected Framework

Data Analytics Lens

Data Analytics Lens: AWS Well-Architected Framework

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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 this 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, cost-effective, and sustainable 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. Also consider best practices and questions that have not been included in this document when designing your architecture. We therefore recommend that you read the AWS Well-Architected Framework whitepaper.

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.

There are many methods for implementing a data platform, therefore there are many options your organization must consider before designing a solution. In this whitepaper, we detail specific architectural approaches that can meet your design objectives. You must consider whether the proposed solution meets your organizational architecture principles and whether your team resources have the experience to implement such a solution.

Custom lens availability

Custom lenses extend the best practice guidance provided by AWS Well-Architected Tool. AWS WA Tool allows you to create your own custom lenses, or to use lenses created by others that have been shared with you.

To determine if a custom lens is available for the lens described in this whitepaper, reach out to your Technical Account Manager (TAM), Solutions Architect (SA), or AWS Support.

Workload context checklist

To understand your business's context better, 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)

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

- 1 – Monitor the health of the analytics application workload
- 2 – Modernize deployment of the analytics jobs and applications

Security

- 3 – Designing data platforms for governance and compliance
- 4 – Implement data access control
- 5 – Control the access to workload infrastructure

Reliability

- 6 – Design resilience for analytics workload
- 7 – Govern data and metadata changes

Performance efficiency

- 8 – Choose the best-performing compute solution
- 9 – Choose the best-performing storage solution
- 10 – Choose the best-performing file format and partitioning

Cost optimization

- 11 – Choose cost-effective compute and storage solutions based on workload usage patterns
- 12 – Build financial accountability models for data and workload usage
- 13 – Manage cost over time

- 14 – Use optimal pricing models based on infrastructure usage patterns

Sustainability

- 15 – Sustainability implementation guidance

Pillars of the Well-Architected Framework

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 Data Analytics Lens. We recommend you also read and apply the guidance found in each Well-Architected pillar. The pillars include topics related to foundational best practices for operational excellence, security, performance efficiency, reliability, cost optimization, and sustainability that are relevant to all workloads.

Pillars

- Operational excellence
- Security
- Reliability
- Performance efficiency
- Cost optimization
- Sustainability

Operational excellence

The operational excellence pillar includes the ability to support development and run workloads effectively, gain insight into your operations, and continually improve supporting processes and procedures that deliver business value.

Best practices

- 1 – Monitor the health of the analytics application workload
- 2 – Modernize deployment of the analytics jobs and applications

1 – Monitor the health of the analytics application workload

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 transferring data for analytics.
☐ BP 1.2	Required	Monitor operational metrics of data processing jobs and the availability of source data.

For more details, refer to the following information:

- AWS Big Data Blog: Monitor data pipelines in a serverless data lake
- 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 transferring data for analytics

Data quality can have an intrinsic impact on the success or failure of your organization's data analytics projects. To avoid committing significant resources to process potentially poor-quality data, your organization should understand the quality of the source data, and monitor the changes to data quality throughout the data pipeline.

Data source validation can often be performed quickly on a subset of the latest data range to look for data defects. Such defects include missing values, anomalous data, or wrong data types that could fail the analytics job completion or lead to completion of the job with inaccurate results.

For more details refer to following document:

- AWS Blog: How to Architect Data Quality on the AWS Cloud
- AWS Blog: Getting started with AWS Glue Data Quality from the AWS Glue Data Catalog

Suggestion 1.1.1 – Implement data quality validation mechanisms

The critical attributes of data quality that should be measured and tracked through your environment are completeness, accuracy, and uniqueness. Validating and measuring your data

quality using metrics is important to build trust in your data, which increases data adoption throughout your organization.

For more details, refer to the following information:

- AWS Big Data Blog: Set up advanced rules to validate quality of multiple datasets with AWS Glue Data Quality
- AWS Big Data Blog: Getting started with AWS Glue Data Quality for ETL Pipelines
- AWS Big Data Blog: Set up alerts and orchestrate data quality rules with AWS Glue Data Quality
- AWS Big Data Blog: Enforce customized data quality rules in AWS Glue DataBrew.
- AWS Big Data Blog: Build a data quality score card using AWS Glue DataBrew, Amazon Athena, and Amazon QuickSight.

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

Alerts and notifications play a crucial role in maintaining data quality because they facilitate prompt and efficient responses to any data quality issues that may arise within a dataset. By establishing and configuring alerts and notifications, you can actively monitor data quality and receive timely alerts when data quality issues are identified. This proactive approach helps mitigate the risk of making decisions based on inaccurate information.

It's usually more efficient to impute missing values, but in other cases it's more efficient to block processing until the data quality issue can be resolved at source.

Suggestion 1.1.3 – Score and share the quality of your datasets

To improve the ongoing trust in data quality and adoption of your organization's datasets, consider creating a data quality matrix that can be accessed by the relevant teams advertising the quality score of your datasets and potential issues with the data. This information can be incorporated in your Data Catalog.

Best practice 1.2 – Monitor operational metrics of data processing jobs and the availability of source data

Data processing pipelines often consist of multiple steps that all need to run in sequence to output the desired data sets and meet business deadlines. Monitoring each job in the pipeline is

key to ensure operational excellence. The operational metrics of the jobs themselves should be monitored, as well as the availability of source data, and that results are produced.

For example, if your pipeline runs on a fixed schedule, and there is no new source data to process, the pipeline may still appear healthy because it runs without failures. Similarly, if the pipeline runs when new source data becomes available, it can appear healthy when no new source data becomes available if you only alert on failed runs.

Suggestion 1.2.1 – Alert when new data has not arrived or become available within the expected time

You should monitor the time when new data arrives or becomes available, and alert when too much time has passed since the last occurrence. Even if the jobs in your data processing pipeline runs flawlessly, the quality of the results depend on the quality and availability of the source data.

In a complex data pipeline it can also be necessary to monitor that one stage produces results within an expected time frame as it affects downstream stages.

Suggestion 1.2.2 – Alert when data processing jobs don’t complete on time or don’t produce results

You should monitor the running time of data processing jobs and alert when too much time has passed since the last completed run. You should also alert if a job does not produce a result. With monitoring and alerts you can discover jobs that fail, and also jobs that fail silently by not producing results.

The expected completion time should be based on the normal running time of the job, with some margin. The margin is needed because the running time of data processing jobs depend on the amount of data they process. Jobs that start as a result of new data becoming available also don’t have a set starting time, which should be factored into the margin.

For very long running jobs it can also be necessary to monitor the start time of jobs, and alert when too much time has passed since the last start. Sometimes it can cause too much delay to wait until the expected completion time before the failure is discovered.

2 – Modernize deployment of the analytics jobs and applications

How do you deploy 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.

Your team should use test automation to verify infrastructure, code changes, and data updates at every stage of your deployment lifecycle. The analytics processing often requires management of complex workflows. It includes job scheduling, managing dependencies between jobs, and monitoring jobs. You also need an orchestration tool for data movement.

ID	Priority	Best practice
☐ BP 2.1	Recommended	Use version control for job and application changes.
☐ BP 2.2	Recommended	Create test data and provision staging environment.
☐ BP 2.3	Recommended	Test and validate analytics jobs and application deployments.
☐ BP 2.4	Recommended	Build standard operating procedures for deployment, test, rollback, and backfill tasks.

For more details, refer to the following information:

- Reference architecture: Deployment Pipeline Reference Architecture
- AWS Big Data Blog: Build, Test and Deploy ETL solutions using AWS Glue and AWS CDK based CI/CD pipelines
- AWS DevOps Blog: Complete CI/CD with AWS CodeCommit, AWS CodeBuild, AWS CodeDeploy, and AWS CodePipeline
- AWS Big Data Blog: AWS serverless data analytics pipeline reference architecture
- AWS Whitepaper: Building a Cloud Operating Model
- AWS Big Data Blog: Build a DataOps platform to break silos between engineers and analysts

Best practice 2.1 – Use version control for job and application changes

Version control systems support tracking changes and the ability to revert to previous versions of an analytics system should changes cause unintended consequences. Your team should version control code repositories for both analytics infrastructure as code (IaC) and analytics applications logic.

Suggestion 2.1.1 – 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. Using these tools, if a new change results in unwanted outcomes, you can easily roll back to the previous code template.

For more details, refer to the following information:

- AWS Whitepaper: Introduction to DevOps on AWS
- AWS Blog: Automate building an integrated analytics solution with AWS Analytics Automation Toolkit

Best practice 2.2 – Create test data and provision 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, test results can be compared to previous versions.

Confirming that the test datasets accurately represent real-world data allows the analytics workload developer to confirm the outcomes from the analytics job, as well as comparing test results to previous versions.

Your organization should use a staging environment for user access testing. Your organization should create logically separated AWS accounts for your development, test, staging, and production environments depending upon your development standards.

For more details, refer to the following information:

AWS Whitepaper: Establishing your best practice AWS environment

Suggestion 2.2.1 – Use a curated dataset to test application logic and performance improvements

Analytics projects that are being developed should use the same curated 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.

To help control access to sensitive data, your organization should use data masking techniques when restoring development data to non-production environments. More information on data minimization techniques can be found in Security.

For more details, refer to the following information:

- AWS Database Blog: Data Masking using AWS DMS (AWS Data Migration Service)
- Amazon Redshift Data Masking: Dynamic data masking (DDM) in Amazon Redshift

Suggestion 2.2.2 – Use a random sample of recent data to validate application edge cases and help ensure that 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 recognize whether your dataset characteristics have shifted, or whether anomalous data has recently been introduced to your data.

For more information, see the AWS Machine Learning Blog: Create random and stratified samples of data with Amazon SageMaker Data Wrangler.

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 – Establish separate staging environments to test changes before going live

Use separate environments, such as development, test, and production, to allow feature development to be introduced without disrupting production systems. Test changes for accuracy and performance before changes are deployed into the production environment.

Suggestion 2.3.2 – Automate the deployment and testing when infrastructure and applications changes are introduced

The deployment of data pipelines and data infrastructure changes should be an automated process. When code is checked into version control, a CI/CD process should run tests and apply the

changes to the staging environment, and once tested and confirmed correct, it should be deployed to the production environment.

You can use the AWS CodePipeline service to define a CI/CD process.

For more details refer to the following information:

- AWS Perspective Guidance: Deploy an AWS Glue job with an AWS CodePipeline CI/CD pipeline
- AWS DevOps Blog: How to unit test and deploy AWS Glue jobs using AWS CodePipeline
- AWS DevOps Blog: 10 ways to build applications faster with Amazon CodeWhisperer

Best practice 2.4 – 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. Using a standard approach also makes remediation easier if a deployment results in unintended consequences.

Suggestion 2.4.1 – Document and use standard operating procedures for implementing changes in your analytics workload

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

Suggestion 2.4.2 – 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.

Security

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

Best practices

- 3 – Designing data platforms for governance and compliance

- 4 – Implement data access control
- 5 – Control the access to workload infrastructure

3 – Designing data platforms for governance and compliance

How do you protect data in your organization's analytics workload? Privacy by Design (PbD) is an approach in system engineering that takes privacy into account throughout the whole engineering process. PbD especially focuses on systems or applications that capture and process personal data. Many countries or political unions enforce data protection regulations. The main data protection regulations are: GDPR (General Data Protection Regulation), CCPA (California Consumer Privacy), LGPD (Lei geral da Protecao de Dados Pessoasis in Brazil), POPIA (South Africa), Australian Privacy Act and DPA (UK Data Protection Act).

As an organization you must have an understanding what data protection regulations you must adhere to and implement them into your solution accordingly. If your organization operates across territories, then you must adhere to multiple data regulations.

This whitepaper covers the common themes shared amongst these regulations; however this is not an exhaustive list. Therefore you must consult your organization's Data Protection Office to determine what additional regional and company-wide data protection and data governance requirements must be implemented.

For more details regarding the different types of data protection regulations, refer to the following:

- GDPR - General Data Protection Regulation Center
- CCPA - California Consumer Privacy Act
- LGPD - The General Data Protection Law
- POPIA - South Africa Data Privacy

ID	Priority	Best practice
☐ BP 3.1	Required	Privacy by design.
☐ BP 3.2	Required	Classify and protect data
☐ BP 3.3	Required	Understand data classifications and their protection policies.

ID	Priority	Best practice
☐ BP 3.4	Required	Identify the source data owners and have them set the data classifications.
☐ BP 3.5	Required	Record data classifications into the Data Catalog so that analytics workload can understand.
☐ BP 3.6	Required	Implement encryption policies.
☐ BP 3.7	Required	Implement data retention policies for each class of data in the analytics workload.
☐ BP 3.8	Recommended	Enforce downstream systems to honor the data classific ations.

For more details, refer to the following information:

- AWS GDPR Center: Introducing the New GDPR Center and "Navigating GDPR Compliance on AWS" Whitepaper
- 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
- AWS Clean Rooms: What is AWS Clean Rooms

Best practice 3.1 – Privacy by Design

Privacy by Design is an approach in system engineering that takes privacy into account throughout the whole engineering process. It especially focuses on systems or applications that capture and process personal data.

There is an increased focus on ensuring that personal data is processed lawfully, fairly, and in a transparent manner in relation to the data subject. Another concern is that the data processing is adequate, relevant, and limited in relation to the purpose for which the information is used.

Suggestion 3.1.1 – Data minimization

Organizations should only receive, process, and store information that is relevant for the task rather than processing all information when only a portion of the file is required. For example, if a client provided a full extract of all information from their source system containing sensitive personal information, and if a portion of the file is deemed irrelevant in meeting the overall project requirements, the remainder of the file should not be stored or processed.

Data minimization coincides with data access controls in that applying data minimization rules can be implemented using data access controls. A suggestion is to create and maintain a data access matrix aligned with your data classification catalogs. This helps ensure that the correct groups of people have access to the right data. As most compliant frameworks encourage evidence that rules have been applied, a data access matrix can demonstrate to auditors that your organization has gone through the proper thought process to determine who can access what information.

Data minimization can be applied at the point of capture. It can also be applied at the point of access by presenting a restricted data model or implementing role-based access controls (RBAC). For more information on controlling data access, see 4 – Implement data access control.

Test and user acceptance test (UAT) environments, as well as training model datasets, must have a restricted dataset and not contain any personal information. If the structure of the data model must remain the same as production, then consider anonymizing or masking information to meet your data minimization requirements.

It is common practice to create test and development environments using a backup of production and restore to the respective development or test environment. If this is the case, anonymization of personally identifiable information (PII) and other sensitive information must occur using inbuilt logic or services such as AWS Glue DataBrew to obfuscate the information.

For more details, refer to the following documentation:

- Amazon Redshift RBAC - Amazon Redshift role-based access controls
- AWS Lake Formation RBAC - Lake Formation role-based access controls
- Amazon Athena RBAC - Amazon Athena fine-grained access controls
- AWS Glue DataBrew - AWS Glue DataBrew Visual Data Preparation

Suggestion 3.1.2 – Anonymization, pseudonymization, and tokenization

Anonymization, pseudonymization, or tokenisation refers to the method of either rendering data anonymous or encoding data in such a manner that the data is no longer identifiable

Suggestion 3.1.2.1 – Anonymization

Anonymization is defined as the process of turning data into a form that does not identify individuals and where identification is not likely to take place.

This results in changing personal data into data that is no longer personal. An important factor in this process is that the anonymization must be irreversible. The anonymized value should be supported by the current field data type, have similar length, and retain some characteristics of the original value. For example, if a Vehicle Registration Number such as `0U51 SMR` was being anonymized, the result would look similar to `BB88 9AA`.

Organizations need the ability to anonymize full datasets as well as single records. Single record anonymization functionality can help deliver right to erasure and meet data retention requirements. In this case, full batch anonymization is typically used when obfuscating development and UAT environments.

The function to anonymize information should support the flexibility to anonymize certain fields, but not all.

Operational databases, reporting databases, and analytical data marts should all be considered for anonymization, although reports and analytical cubes should never typically contain PII information regardless.

Audit the reason why information was anonymized, for example, data portability, or data retention removal. The time, date, and user ID of when and who the anonymization process has affected should be recorded in an audit table.

For more details, see AWS Big Data Blog: Anonymize and manage data in your data lake with Amazon Athena and AWS Lake Formation

Suggestion 3.1.2.2 – Pseudonymization

Pseudonymized data is not the same as anonymized data.

When data has been pseudonymized, it still retains a level of detail in the target data that allows tracking back of the data to its original state. With anonymized data, the level of detail is reduced rendering a reverse compilation impossible. Pseudonymization is the processing of personal data

in such a way that the data can only be attributed to a specific data subject by using additional information. To pseudonymize a dataset, the additional information must be kept separately and subject to technical and organizational measures to ensure non-attribution to an identified or identifiable person.

In summary, pseudonymized data is a privacy-enhancing technique where directly identifying data, such as IP addresses and contact information, are held separately and securely from processed data to ensure non-attribution. Similar to anonymization, referential integrity must not be affected. Therefore, both of the following are required: an audit trail of the pseudonymization process, and a pseudonymization function that supports both single item and batch processing.

For more detail, see Amazon Redshift Data Masking.

Suggestion 3.1.2.3 – Tokenization

Tokenization, when applied to data security, is the process of substituting a sensitive data element with a non-sensitive equivalent. This is referred to as a token, which has no extrinsic or exploitable meaning or value. The token is a reference that maps back to the sensitive data through a tokenization system. Tokenization is typically used in finance to tokenize the payment account number (PAN).

For more details, refer to the following information:

- AWS Blog – AWS Glue DataBrew detection data masking transformations
- AWS Blog - Data Tokenization with Amazon Redshift and Protegrity

Suggestion 3.1.3 – Rights of the individual, citizen, or subject

Your organization should consider the process to address the rights of the individual, citizen, or subject for their respective regional regulation.

Suggestion 3.1.3.1 – Subject Access Request (SAR)

This particular right is for an individual to request information from the data controller, that is, how their personal data is being processed. If an individual's information is being processed, the personal data and associated metadata must be provided to that individual.

If the individual's information is stored in a database, then an automated process, such as a stored procedure or User-Defined Function (UDF), should be developed to answer the Subject Access Request (SAR). There will, however, be situations when the individual's information is stored in

Amazon S3. If the information is stored in Amazon S3, the proposed solution to identify which S3 object contains the respective information is to build a lookup table in a database containing the reference number, individual contact details, and the S3 object location. This approach allows your organization to ingest the information into Amazon EMR, infer the schema using Apache Spark, and extract the information required to fulfill the request. Alternatively, your organization must process all S3 objects to identify the information to fulfill the request.

If your regional regulations require that your organization handle a right to data portability request, then the SAR logic can double up to support that as well.

For more details, see Apache Spark Documentation - Inferring the Schema Using Reflection

Suggestion 3.1.3.2 – Right to be forgotten or erasure

Individuals have the right to erasure (the right to be forgotten), where an individual can request that all of their personal data is erased by the data controller organization. In some countries, there are instances where the data controller can refuse to comply with a right to erasure request, such as where the data is used for financial governance.

The right to erasure does not strictly mean that the individual's information must be deleted. Instead, it can be permanently masked so that the personal data is no longer in the clear and the update is irreversible.

The organization must consider all data repositories when responding to a SAR as an individual's information can reside in back up and source system databases. All these records must have the individual's information removed or anonymized.

If there are concerns about the impact of database referential integrity being affected by removing the individual's information, then you can consider anonymization of the specific data attributes for the given individual. There are benefits to anonymization, such as being able to maintain an audit history of what actions have been performed against the individual by referencing a system ID. The same steps that are performed in production environments must also be run in UAT, development, OLTP, and back up repositories.

The schedule of running the procedure in the other environments depends on the refresh schedules of those other environments.

Best practice 3.2 – 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.

Best practice 3.3 – 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 necessarily copies and shares data between operations and systems, we recommend that access be controlled to certain data classifications. Such a data protection strategy helps to prevent data loss, theft, and corruption, and helps to minimize the impact caused by malicious activities or unintended access.

Suggestion 3.3.1 – Identify classification levels

Use the Data Classification whitepaper to help you identify different classification levels. Four common levels used are restricted, confidential, internal, and public, however, these levels can vary based on the industry and compliance requirements of your organization.

Suggestion 3.3.2 – Define access rules

The data owners should define the data access rules based on the sensitivity and criticality of the data. For example, with AWS Lake Formation, you can define and enforce access controls that operate at the table, column, row, and cell level for all the users that access your data lake.

For more details, refer to the following information:

- AWS Security Blog: How to scale your authorization needs by using attribute-based access control with S3.
- AWS Big Data Blog: Create a secure data lake by masking, encrypting data, and enabling fine-grained access with AWS Lake Formation.
- 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 3.3.3 – 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 development and test resources from production ones from AWS account level or from resource levels.

For more details, refer to the following 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 3.3.4 – Identify sensitive information and define protection policies

Discover sensitive data by using custom data identifiers in Amazon Macie or using AWS Glue sensitive data detection. 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.

For more details, refer to the following information:

- AWS Blog: Introducing PII data identification and handling using AWS Glue DataBrew
- AWS Blog: Create a secure data lake by masking, encrypting data, and enabling fine-grained access with AWS Lake Formation
- AWS Info: AWS Glue detect and process sensitive data

Best practice 3.4 – Identify the source data owners and have them set the data classifications

Identify the owners of the source data, like business data owners, and agree what level of protection is required for the data within the analytics platform.

Data classifications follow the data as it moves throughout the analytics workflow to ensure that the data is protected, and to determine who and what 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. These classifications include *restricted*, *confidential*, and *sensitive*.

Suggestion 3.4.1 – Assign owners per each dataset

A dataset, or a table in relational database, is a collection of data. A Data Catalog is a collection of metadata that helps centralize share and search information about the data within your platform. In addition to assigned classifications, this capability allows teams to search for data assets and decide whether the data asset is valuable for their analyze or data science workload.

The administrator of the analytics workload should know who are the owners for each dataset, and should assign the dataset ownership in the Data Catalog.

Suggestion 3.4.2 – 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 classified as highly sensitive has permission issues within the organization, you might have to talk to the dataset owners and have them resolve the issues.

Suggestion 3.4.3 – 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 3.5 – 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 protect the data effectively, 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), then the analytics workload should be able to determine which data is classified as confidential by referencing its data catalog.

Suggestion 3.5.1 – Use tags to indicate the data classifications

Use a tagging ontology to designate the classification of sensitive data in data stores with a data catalog. A tagging ontology allows discoverability of data sensitivity without directly exposing

the underlying data. They also can be used to authorize access in tag-based access control (TBAC) schemes.

For more details, refer to the following information:

- AWS Lake Formation Developer Guide: What Is AWS Lake Formation?
- AWS Whitepaper: Tagging Best Practices
- AWS Lake Formation: Easily manage your data lake at scale using AWS Lake Formation Tag-based access control

Suggestion 3.5.2 – 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 has come from, what changes occurred to the data, and which downstream systems have access to it. Your organization should be able to discover, record, and visualize the data lineage from source to target systems.

For more details, refer to the following information:

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

Best practice 3.6 – Implement encryption policies

Data encryption is a way of translating data from plaintext (unencrypted) to ciphertext (encrypted). Encryption is a critical component of a *defense in depth* strategy. Therefore, it is highly recommended that your organization implement a well-designed encryption and key management system by separating access to the decryption key from access to your data to provide data security.

Suggestion 3.6.1 – Implement encryption policies for data at rest and in transit

Each analytics service provides different types of encryption methods. Review the viable encryption methods of your solutions and implement as necessary.

For more details, refer to the following information:

- AWS Key Management Service (AWS KMS) encryption best practices

- 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 (APN) Blog: Data Tokenization with Amazon Redshift and Protegrity

Best practice 3.7 – 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. More information on data retention can be found in Sustainability .

Suggestion 3.7.1 – Create backup requirements and policies based on data classifications

Data backup should be based on business requirements, such as recovery point objective (RPO), recovery time objective (RTO), data classifications, and the compliance and audit requirements.

Suggestion 3.7.2 – 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 their retention requirements.

For more details, refer to the following information:

- 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

Suggestion 3.7.3 – Create data version requirements and policies

Implement a process that captures the data version to address, based on compliance, security, and operational requirements.

For more details, refer to the following information:

- AWS Storage Blog: Reduce storage costs with fewer noncurrent versions using Amazon S3 Lifecycle
- AWS Storage Blog: Simplify your data lifecycle by using object tags with Amazon S3 Lifecycle
- AWS Database Blog: Implementing version control using Amazon DynamoDB

Best practice 3.8 – Enforce 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 be encrypted using customer managed private keys in AWS Key Management Service (AWS KMS), then the downstream systems should also acknowledge and implement such a data protection policy.

This helps to ensure that the data is protected throughout the data pipelines.

Suggestion 3.8.1 – Have a centralized, shareable catalog with cross-account access to ensure that data owners manage permissions for downstream systems

Downstream systems can run on independent AWS accounts, different from the AWS account running the majority of the analytics workload. Downstream systems should be able to discover the data, acknowledge the required data protection policies, and enforce those policies across the analytics platform.

To allow the downstream systems to use the data from analytics workload, the analytics workload should provide cross-account access based on least privileges for each dataset.

For more details, refer to the following information:

- 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 3.8.2 – 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 which systems are eligible to process various classes of data, periodically verify that each downstream system's data processing eligibility levels are correct and the list of data that it accesses are appropriate.

4 – Implement data access control

How do you manage access to data within your organization's source, analytics, and downstream systems?

An analytics workload is a centralized repository of data from different source systems. As the analytics workload owner, you should honor the source systems' access management policies when connecting to, and ingesting from, the source systems.

ID	Priority	Best practice
☐ BP 4.1	Required	Allow data owners to determine which people or systems can access data in analytics and downstream workloads.
☐ BP 4.2	Required	Build user identity solutions that uniquely identify people and systems.
☐ BP 4.3	Required	Implement the required data authorization models.
☐ BP 4.4	Recommended	Establish an emergency access process to ensure that admin access is managed and used when required.
☐ BP 4.5	Recommended	Track data and database changes.

For more details, refer to the following documentation:

- AWS Lake Formation Developer Guide: Lake Formation Access Control Overview
- Amazon Athena User Guide: AWS Identity and Access Management in Amazon Athena
- Amazon Athena User Guide: Enabling Federated Access to the Amazon 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 4.1 – 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 4.1.1 – Identify data owners and assign roles

Data ownership 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 4.1.2 – Identify permission using a 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 to describe what actions they can perform. Below is a sample matrix for two users, and two roles for two schemas with a table in them:

Table 1: Example Access Control Matrix for Users and Roles

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 permissions that are required by various resources and to 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 4.2 – Build user identity solutions that uniquely identify people and systems

To control data access effectively, 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 person or system.

For more details, refer to the following information:

- 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 OpenSearch 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 4.2.1 – 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 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 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 information:

- 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 for Amazon EMR Studio

Best practice 4.3 – Implement the required data access authorization models

User authorization determines what actions that 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 must 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 4.3.1 – 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, see AWS Big Data Blog: Restrict access to your AWS Glue Data Catalog with resource-level IAM permissions and resource-based policies

Suggestion 4.3.2 – 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 information:

- AWS Big Data Blog: Validate, evolve, and control schemas in Amazon MSK and Amazon Kinesis Data Streams with AWS Glue Schema Registry.
- Amazon Redshift: Amazon Redshift announces support for Row-Level Security (RLS) Streams with AWS Glue Schema Registry.

Suggestion 4.3.3 – 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 information:

- AWS Big Data Blog: Allow fine-grained permissions for Amazon QuickSight authors in AWS Lake Formation
- Amazon Redshift: Role-based access controls
- 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 4.4 – Establish an emergency access process to ensure that admin access is managed and used when required

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 4.4.1 – Ensure that risk analysis is performed 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, or high) and the size of the business impact (small, medium, or large).

For example, after 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.

Best practice 4.5 – Track data and database changes

Data auditing involves monitoring a database to track the actions of a user or process, and to audit the changes that have occurred to the data.

Suggestion 4.5.1 – Database triggering for data auditing

A database trigger is procedural code that is automatically run in response to certain events on a particular table or view in a database. Database triggers can then be used to update an audit

table with the changes that have occurred. The types of information that should be included in the auditing process include: the original and updated value of what has been updated, the process or stored procedure that made the update, and the time and date the update occurred.

Suggestion 4.5.2 – Enable advanced auditing

If your database engine supports auditing as a native feature, you should enable the feature to record and audit database events such as connections, disconnections, tables queried, or types of queries issued.

Suggestion 4.5.3 – AWS Lake Formation time travel queries

Apache Iceberg and Apache Hudi provide a high-performance data lake table format that works just like a SQL table. Iceberg and Hudi make it simple to manage your data lake information and support SQL type analytics. Data that is managed by Iceberg or Hudi is version-controlled, therefore there is a complete history of all data updates. A good example is if you need to know the status of an individual at a certain time, then a time travel query allows you to select a date range to return the value that existed at that time, rather than the current value.

For more details, see Use the AWS Glue connector to read and write Apache Iceberg tables with ACID transactions and perform time travel.

Suggestion 4.5.4 – Change Data Capture (CDC)

CDC records `INSERT`s, `UPDATE`s, and `DELETE`s applied to relational database tables, and makes a log available of which relational database objects changed, where, and when. These change tables contain columns that reflect the column structure of the source table you have chosen to track, along with the metadata required to understand the changes that have been made.

For more details, refer to the following information:

- AWS CloudTrail - Secure Standardized Logging
- Amazon RDS Aurora - Advanced Auditing with an Amazon Aurora
- Amazon RDS Aurora - Configuring an audit log to capture database activities for Amazon RDS
- AWS Database Migration Service (AWS DMS) AWS Database Migration Service

5 – 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 data distribution. Ensuring the

environment is accessible with the least permissions necessary is essential in delivering a secure platform. Automate the auditing of environment changes and generate alerts in case of abnormal environment access.

ID	Priority	Best practice
☐ BP 5.1	Required	Prevent unintended access to the infrastructure.
☐ BP 5.2	Required	Implement least privilege policies for source and downstream systems.
☐ BP 5.3	Required	Monitor the infrastructure changes and the user activities against the infrastructure.
☐ BP 5.4	Required	Secure the audit logs that record every data or resource access in analytics infrastructure.

Best practice 5.1 – Prevent unintended access to the infrastructure

Grant least privilege access to infrastructure to help prevent inadvertent or unintended access to the infrastructure. For example, 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. To reduce the risk of inadvertent access, define the network boundaries of the analytics systems and only allow intended access.

Suggestion 5.1.1 – 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 5.2 – 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 5.2.1 – Ensure that permissions are least for the action performed by user/system

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

For more details, refer to the following information:

- 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 5.2.2 – Implement the two-person rule to prevent accidental or malicious actions

Even if you have implemented the least privilege policies, someone must have critical permissions for the business, such as the ability to delete 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 5.3 – 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. This is to ensure that such changes are deliberate and the infrastructure is still protected.

Suggestion 5.3.1 – 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 that 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 5.3.2 – Monitor the user activities against the infrastructure

You want to know who is changing the infrastructure and when, so that you can see that 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 information:

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

Best practice 5.4 – Secure the audit logs that record every data or resource access in analytics infrastructure

Logs are an audit trail of events and should be stored in an immutable format for compliance purposes. 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 even 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 5.4.1 – 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 fault-tolerant persistent storage. This helps ensure that you have complete audit logs for security and compliance purposes.

For more details, refer to the following information:

- AWS Management and Governance Blog: AWS CloudTrail Best Practices
- Amazon Redshift Cluster Management Guide: Database audit logging
- Amazon OpenSearch Service (successor to Amazon OpenSearch 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 encompasses the ability of a workload to perform its intended function correctly and consistently when it's expected to. This includes the ability to operate and test the workload through its total lifecycle. This reliability pillar provides in-depth, best practice guidance for implementing reliable analytics workloads on AWS.

Best practices

- 6 – Design resilience for analytics workload
- 7 – Govern data and metadata changes

6 – Design resilience for analytics workload

How do you design analytics workloads to withstand and mitigate failures?

ID	Priority	Best practice
☐ BP 6.1	Required	Create an illustration of data flow dependencies.

ID	Priority	Best practice
☐ BP 6.2	Required	Monitor analytics systems to detect analytics or extract, transform and load (ETL) job failures.
☐ BP 6.3	Required	Notify stakeholders about analytics or ETL job failures.
☐ BP 6.4	Recommended	Automate the recovery of analytics and ETL job failures.
☐ BP 6.5	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 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 6.1 – Create an illustration of data flow dependencies

Work with business stakeholders to create a visual illustration of the data pipeline. Identify the systems that interact with each dependency. The key architecture components that are expected to be captured are data acquisition, ingestion, data transformation, data processing, data storage, data protection and governance, and data consumption. All system dependencies need owners. Agree within your organization who owns which dependency.

Best practice 6.2 – Monitor analytics systems to detect analytics or extract, transform and load (ETL) job failures

Detect extract, transform, and load (ETL) and analytics job failures as soon as possible. Pinpointing where and how the error occurred is critical for notifications and corrective actions.

Suggestion 6.2.1– Monitor and track job errors from different levels, including infrastructure, ETL workflow, and ETL application code

Failures can occur at all levels of the analytics system. Each task in the analytics workload should be instrumented to provide metrics indicating the health of the task. Monitor the emitted metrics and raise alarms if any components fail. Create dashboards to visualize metrics and govern access to them.

For more details, refer to the following:

- Visualize data warehouse metrics: Query and visualize Amazon Redshift operational metrics using the Amazon Redshift plugin for Grafana
- Visualize Amazon EMR metrics: Monitor Amazon EMR on Amazon EKS with Amazon Managed Prometheus and Amazon Managed Grafana

Suggestion 6.2.2 – 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 6.2.3 – 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. If possible, roll-back the committed data and restart your job.

For more details, see AWS Glue: Overview of Data Quality in AWS Glue.

Suggestions 6.2.4 – Classify the severity of the job failures based on the type of failure and the business impact

Classifying the severity of different job failures helps you prioritize remediation and guide the notification requirements to key stakeholders. Classification of jobs can be agreed upon based on importance and the impact the failure has on meeting internal and external SLAs.

Best practice 6.3 – 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 about the job failure as soon as possible is important for remediation actions needed. Stakeholders may include IT operations, help desk, data sources, analytics, and downstream workloads.

For more details, see AWS Well-Architected: Design your Workload to Withstand Component Failures

Suggestions 6.3.1 – Establish automated notifications to predefined recipients

Use services such Amazon Simple Notification Service (Amazon SNS) to send automated emails, SMS alerts, or both in the event of failure. Store the alert logs in an immutable data store for future reference.

Suggestions 6.3.2 – Do not include sensitive data in notifications

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

For more details, see AWS Glue: Detect and process sensitive data.

Suggestions 6.3.3 – 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. That same ticket can automatically be resolved if the analytics system recovers on retry.

Suggestions 6.3.4 – 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 troubleshoots and attempts to recover the failed job, if possible. It is also helpful to notify the IT help desk of system failures that have an end user impact. These can include issues with the data warehouse used by the business intelligence (BI) analysts.

Suggestions 6.3.5 – Notify downstream systems of data freshness

Monitor data updates as this gives process and application information when data becomes stale. Stale data can lead to misreporting due to the correct values being stale and not current.

Best practice 6.4 – Automate the recovery of analytics and ETL job failures

Many factors can cause analytics and ETL jobs to fail. Job failures can be recovered using automated recovery solutions, however, others might require manual intervention. Designing and implementing an automated recovery solution can help reduce the impact of the job failures and streamline IT operations.

Suggestions 6.4.1– Discover recovery procedures that work for multiple failure types

Configure automatic retries to handle intermittent network disruptions. Configure managed scaling to ensure that there are sufficient resources available for jobs to complete within specific time limits.

Suggestions 6.4.2 – 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 process has attempted. Limit the number of reruns to avoid unnecessary reruns and resources. Track the number of recovery attempts and outcomes to identify failure trends and drive future improvements.

Suggestion 6.4.3 – Design the job recovery solution based on the delivery SLA

Build systems that can meet SLA requirements even if jobs must be retried or manually recovered. Consider the service-level agreements of the different services that you use, and monitor the performance of your jobs against your organization’s internal SLAs.

Suggestion 6.4.4 – Consider idempotency when designing ETL jobs

To avoid unexpected outcomes when automatically rerunning pipelines such as duplicated or stale data, enforce idempotency where possible. Idempotent ETL jobs can be rerun with the same result or outcome. Some strategies to achieve this are the overwriting method (for example, Spark overwrite) and the delete-write method (deleting existing data prior to writing it to ensure that there are no duplicates or stale data), although deletion should be applied with caution.

Best practice 6.5 – Build a disaster recovery (DR) plan for the analytics infrastructure and the data

Discuss with business stakeholders to understand maximum amount of data loss (RPO) and maximum amount of service loss (RTO).

Suggestion 6.5.1 – Confirm the business requirement of the disaster recovery (DR) plan

Agree with the business shareholders what the internal and external SLAs are for your analytics processes. For example, not all business reports are business critical so it's important that your DR plans are aligned with the severity of the outage.

Suggestion 6.5.2 – Design the disaster recovery (DR) solution for each layer of the solution

Review the architecture for your data and analytics pipeline and select the DR pattern that meets your DR requirements, working backwards from the most important information that must be saved in the event of a DR scenario, to the least important.

Suggestion 6.5.3 – Implement and test your backup solution based on the RPO and RTO

Backup solutions must be implemented to reduce data loss. Test your backup to ensure it is performing correctly by periodically restoring the data and validating the results.

7 – 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 also makes downstream systems harder to manage data quality issues of their own.

ID	Priority	Best practice
☐ BP 7.1	Required	Build a central Data Catalog to store, share, and track metadata changes.
☐ BP 7.2	Required	Monitor for data quality anomalies.
☐ BP 7.3	Required	Trace data lineage.

Best practice 7.1 – 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. A Data Catalog is often required for auditing and compliance but by incorporating business context to a Data Catalog, it allows users in the organization to discover data assets using business terms rather than technical naming conventions.

Suggestion 7.1.1 – 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. The AWS Glue Schema registry allows you to centrally discover and control data schemas. You can create a schema contract between producers and consumers to improve data consumer awareness to data format changes.

Suggestion 7.1.2 – Capture and publish business metadata of your data assets

Capturing business metadata and publishing it with metadata assets is essential for data consumers and data stewards alike. Metadata such as regulatory compliance statuses, data classification, and other important data governance characteristics, guides consumers on how to best process the data and informs data governance processes conducted by data stewards. Establishing a business glossary across the organization creates a collection of business terms that can be associated with the data assets. This ensures that business definitions are common across the organization.

For more details, see AWS Data Zone: Governed Analytics.

Best practice 7.2 – Monitor for data quality anomalies

Data quality is critical for organizations to accurately measure important business metrices, bad data can impact the accuracy of analytics insights and ML predictions. Monitor data quality and detect data anomalies as early as possible.

For more details, see AWS Glue: Getting started with AWS Glue Date Quality.

Suggestion 7.2.1 – 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 to prevent bad data from propagating downstream.

Suggestion 7.2.2 – Understand the nature of your data and determine the types of data anomalies that must be monitored and fixed based on the business requirements

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

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

Suggestion 7.2.3 – Select an existing data quality solution or develop your own based on the requirements

There are data quality solutions that can only detect single field data quality issues. Other solutions can handle complex stateful data quality issues related to multiple fields.

Best practice 7.3 – Trace data lineage

Have a clear understanding about where your organization's data is coming from, how the data is transformed, who and what systems have access to the data, and how the data is used, is critical to increasing the business value of data. To achieve this goal, data lineage should be tracked, managed, and visualized.

Suggestion 7.3.1 – Track and control data lineage information

Data lineage information should include where data has come from, where the data is going, and who has access to the data. Data changes and the business logic used should also be tracked in the data lineage.

Suggestion 7.3.2 – Use visualization tools to investigate data lineage

Data lineage can become complicated when multiple systems are interacting with each other. Building a data lineage tool to visualize data lineage can reduce troubleshooting time and help identify downstream dependencies.

Suggestion 7.3.3 – Build a data lineage report to satisfy compliance and audit requirements

If some derestriction data lineage is required for compliance or audit purposes, your organization should either build a data lineage process using AWS services or investigate third-party applications.

For more details, refer to the following information:

- AWS data lineage blog**:** Build data lineage for data lakes using AWS Glue, Amazon Neptune, and Spline

Performance efficiency

The performance efficiency pillar focuses on the efficient use of resources to meet requirements as demand changes and technologies evolve. 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.

Performance optimization should start with your organization’s requirements, such as the business users of the analytics workload. Let the business stakeholders define the performance requirements and SLAs that must be met, then determine the computing requirements meeting their performance needs.

Best practices

- 8 – Choose the best-performing compute solution
- 9 – Choose the best-performing storage solution

- 10 – Choose the best-performing file format and partitioning

8 – Choose the best-performing compute solution

How do you select the best-performing 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 8.1	Recommended	Identify analytics solutions that best suit your technical challenges.
☐ BP 8.2	Recommended	Provision compute resources to the location of the data storage.
☐ BP 8.3	Recommended	Define and measure the computing performance metrics.
☐ BP 8.4	Recommended	Continually identify under-performing components and fine-tune the infrastructure or application logic.

For more details, refer to the following information:

- 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 8.1 – Identify analytics solutions that best suit your technical challenges

AWS has multiple analytics processing services that are built for specific purposes. These include Amazon Redshift for data warehousing, Amazon Kinesis for streaming data, and Amazon

QuickSight for data visualization. Your organization should consider each step of the data analytics process as an opportunity to identify the right tool for the job.

Suggestion 8.1.1 – Identify the requirements based on the collected business metrics

Applications and services are designed to overcome specific challenges. It's essential that your organization identifies the right tool for the right job to meet your business and technical requirements. Choosing inappropriate technology can introduce performance issues, especially when processing data at scale.

For more details, refer to the following information:

- AWS Right Tool for the Job: Databases on AWS: The Right Tool for the Right Job
- AWS Right Tool for the Job: How to Choose the Right Database

Best practice 8.2 – Provision the compute resources to the location of the data storage

Data analytics workloads require moving data through a pipeline, either for ingesting data, processing intermediate results, or producing curated datasets. It is often more efficient to select the location of data processing services near where the data is stored. This approach is preferred instead of 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.

This extends to considering where your compute and storage are located at the Availability Zone level. Co-locating in the same Availability Zone allows fast, lower latency access. It is still important, however, to replicate data across zones when required.

Suggestion 8.2.1 – Migrate or copy primary data stores from on-premises environments to AWS so that cloud compute and storage are closely located

Minimize duplication of data when transferring datasets from on-premises storage 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. For optimal performance, keep your data and analytics systems in the same AWS Region. If they are in separate Regions, relocate one of them.

Suggestion 8.2.2 – Consider where your analytics resources are placed

For optimal performance, your organization should align the location of the data with the location of the resources that process it. Where possible, your organization should consider using a permanent Region for all data analytics processing as this will help with data transferring overhead.

Suggestion 8.2.3 – Consider the use of provisioned compared to serverless offerings to match your workload pattern

When considering services for ingesting, transforming, and analyzing your data, there is often the choice between provisioned or serverless solutions. There are many trade-offs and potential advantages of each, but from a performance perspective, it can be beneficial to use serverless offerings when your workloads are consistently and unpredictably spikey. Whereas provisioned deployments may offer advantages when you have more stable, predictable workloads.

Best practice 8.3 – 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 take the following approach. Define the performance as the Amazon EMR job runtime from the launch of the EMR cluster, process the job, then shut down the cluster. As another example, if the computing solution is an Amazon Redshift cluster that is shared by a business unit, you can define the performance as the runtime duration for each SQL query.

Suggestion 8.3.1 – Define performance efficiency metrics

Collect and use metrics to scale the resources to meet business requirements. By doing so, your team can track unexpected spikes to make future improvements.

Suggestion 8.3.2 – Continually 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. Performance fine-tuning varies for each AWS service, but generally, optimizing queries or workloads can enhance performance without necessitating infrastructure modifications. For example, if it is an Amazon EMR cluster running a Spark application, you could explore tuning your Spark configuration. If after fine-tuning you still need more performance, you can change to a larger cluster instance type, or increase the number of cluster nodes.

For an Amazon Redshift cluster, you can fine-tune the SQL queries that are running below the performance criteria and if required, increase the number of cluster nodes to increase parallel computing capacity.

9 – 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 influenced by several factors such as:

- Compute engine (Amazon EMR, Amazon Redshift, Amazon RDS, and so on)
- Access patterns (random or sequential)
- Required throughput
- Access frequency (online, offline, archival)
- CRUD (create, read, update, delete) operation requirements
- Data durability requirements
- Archival requirements

Choose the best-performing storage solution for your analytics workload's own characteristics.

ID	Priority	Best practice
☐ BP 9.1	Highly recommended	Identify critical performance criteria for your storage workload.
☐ BP 9.2	Highly recommended	Identify and evaluate the available storage options for your compute solution.
☐ BP 9.3	Recommended	Choose the optimal storage based on access patterns, data growth, and the performance requirements.

For more details, refer to the following information:

- 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 9.1 – Identify critical performance criteria for your storage workload

In data analytics, throughput is often a constraining factor to enable your workloads to run effectively. Throughput is measured by the amount of information that has successfully moved through the network, compute, or storage layers. Improving throughput in each of these layers generally results in better query performance.

Suggestion 9.1.1 – Use performance monitoring tools to determine if the analytics system performance is limited by compute, storage, or networking

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.

Best practice 9.2 – Identify and evaluate 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 relevant storage options to determine the most performance efficient solution that meets business requirements.

Suggestion 9.2.1 – Review the available storage options for the analytics services being considered

There are often multiple storage options available for each service, each offering different characteristics and potentially performance benefits. It is important to review these available options and determine which may best fit your requirements.

For example, Amazon EMR provides local storage via HDFS file system and Amazon S3 as an external storage via EMRFS. For more information, refer to the AWS documentation 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 Developer Guide: Managing indices in Amazon OpenSearch Service
- Amazon Aurora User Guide: Overview of Aurora storage

Suggestion 9.2.2 – Evaluate the performance of the selected storage option

To ensure that the overall analytics system design meets your non-functional requirements, evaluate the performance by running simulated real-world tests in a test environment.

Best practice 9.3 – Choose the optimal storage based on access patterns, data growth, and the performance requirements

Storage options for data analytics can have performance tradeoffs based on access patterns and data size. For example, in Amazon S3, can be much more efficient to retrieve a smaller number of larger objects, as opposed to a larger number of smaller 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 9.3.1 – 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.

10 – 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 data partitioning for data-at-rest can have a large impact on the overall analytics workload efficiency.

ID	Priority	Best practice
☐ BP 10.1	Recommended	Select format based on data write frequency and patterns for append-only compared to in-place update.
☐ BP 10.2	Recommended	Choose data formatting based on your data access pattern

ID	Priority	Best practice
☐ BP 10.3	Recommended	Utilize compression techniques to both decrease storage requirements and enhance I/O efficiency.
☐ BP 10.4	Recommended	Partition your data to enable efficient data pruning and reduce unnecessary file reads.

For more details, refer to the following information:

- 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 10.1 – Select format based on data write frequency and patterns for append-only compared to in-place update

Review your data storage write patterns and performance requirements for streaming and batch workloads. Streaming workloads may require you to write smaller files at a higher frequency compared to batch workloads. This enables your streaming applications to reduce latency but can impact read and write performance of the data.

Suggestion 10.1.1 – Understand your analytics workload data's write characteristics

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

There are also table formats available, such as Apache Hudi, Apache Iceberg and Delta Lake that can, amongst other capabilities, provide transactional semantics over data tables in Amazon S3. These formats can also provide improved query times through the use of additional metadata. For more detail on getting started with these formats, see Introducing native support for Apache Hudi, Delta Lake, and Apache Iceberg on AWS Glue for Apache Spark, Part 1: Getting Started.

Suggestion 10.1.2 – Avoid querying data stored in many small files

Rather than running queries over many small data files, periodically combine the small files into a single larger compressed file for analytics. This approach provides better data retrieval performance when using analytics services. Keep in mind that in streaming use cases there is a tradeoff between latency and throughput, as time is required to batch records. The production of larger files can be done as a post process job rather than necessarily at the point of ingestion.

Best practice 10.2 – Choose data formatting based on your data access pattern

Choosing the right data type for your workload is important. There are many different data types available to support your workload. Choosing the right format is a key step in the performance optimization of your analytics workloads.

Suggestion 10.2.1 – Decide the correct data format for your analytics workload

You can work on unstructured, semi-structured, and structured data formats (CSV, JSON, or columnar formats such as Apache Parquet and Apache ORC) with your data stored in Amazon S3 by using Amazon Athena, which lends itself to querying data as-is without the need for data preparation or ETL processes.

You should also consider compression when choosing data formats. Efficient compression can help queries run faster and reduce cost. It can also lead to reductions in the amount of data stored in a storage layer, alongside improved network and I/O throughput. For more information on when to use compression, see 10.3.2.

Using splittable formats is also an option. These formats allow individual files to be broken up so that they can be processed in parallel by multiple workers. Similarly to compression, this can also lead to reductions in query time. Often, you need to choose between compression or splittable formats because applying both is currently not well supported for analytics workloads.

Suggestion 10.2.2 – API-driven data access pattern constraints, such as the amount of data retrieved per API call, can impact overall performance

If you are calling APIs to ingest, transform or access data, many implement a maximum amount of data or records that can be returned in a call. So, your solution may need to page through and make subsequent API calls to retrieve all results. If a large amount of data is returned this can lead to a long amount of time being spent retrieving the data in this manner. Most APIs have limits and constraints, such as number of calls in a particular time limit, so it is important to consider this, and relevant strategies for dealing with these conditions.

Result caching on API sources can help speed up reads if the same or similar data is frequently queried. Using asynchronous methods can help avoid blocking calls in your processing that would otherwise have to wait for synchronous operations to complete.

Suggestion 10.2.3 – Use data, results, and query cache 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, DynamoDB Accelerator (DAX), API gateway caching, Athena query result reuse, Amazon Redshift Advanced Query Accelerator (AQUA), or other relevant caching services.

Best practice 10.3 – Utilize compression techniques to both decrease storage requirements and enhance I/O efficiency

Store data in a compressed format to reduce the 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.

We recommend that your organization test the performance and storage overhead of both uncompressed and compressed datasets to determine best fit prior to implementing this approach.

Suggestion 10.3.1 – Compress data to reduce the transfer time

When storage read/write performance becomes a bottleneck, use compression to reduce data transfer time. Consider the tradeoffs between compute time needed to perform compression and decompression versus the storage I/O bottleneck in your estimates of overall improvements in performance efficiency.

Suggestion 10.3.2 – Evaluate the available compression options for each resource of the workload

Compressing data can improve the performance as there are fewer bytes transferred between the disk and compute layers. The trade-off using this approach is that it requires more compute for data compression and decompression. You can, however, obtain a net efficiency improvement if compression performs as well as or better than uncompressed data transfer time. Compression also requires much less storage, depending on the data type in use, thus saving on data storage latency and costs.

Best practice 10.4 – Partition your data to enable efficient data pruning and reduce unnecessary file reads

Storing your data in structured partitions will allow compute to identify the location of only that portion of the data relevant to the query. Determine the most frequent query parameters and store this data in the appropriate location suited to your data retrieval needs. For example, if an analytics workload regularly generates daily, weekly, and monthly reports, then store your data using partitions with a year/month/day format.

Suggestion 10.4.1 – Partition data to support the most common query predicates

When your query uses a particular predicate in a WHERE clause, if your data is partitioned according to the field then the query engine can prune the data that it needs to look at and go directly to the relevant data partition. This means a full table scan is avoided, meaning faster performance and lower query cost.

Suggestion 10.4.2 – Store data partitioned based on time attributes with earlier data stored in tiers that are accessed infrequently

Use the tiering capabilities of the storage service to put infrequently-accessed data into the tier that is most appropriate for the workload. For example, in an Amazon Redshift data warehouse, data that is accessed infrequently can be stored in Amazon S3. Then you can query it with Amazon Redshift Spectrum, while more 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. Cost optimization is a key effort, 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 should 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 to perform a return on investment (ROI) estimation for the analytics portfolio as a whole.

Best practices

- 11 – Choose cost-effective compute and storage solutions based on workload usage patterns
- 12 – Build financial accountability models for data and workload usage
- 13 – Manage cost over time
- 14 – Use optimal pricing models based on infrastructure usage patterns

11 – 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 11.1	Recommended	Decouple storage from compute.
☐ BP 11.2	Recommended	Plan and provision capacity for predictable workload usage.
☐ BP 11.3	Recommended	Use On-Demand Instance capacity for unpredictable workload usage.
☐ BP 11.4	Recommended	Use auto scaling where appropriate.

For more details, refer to the following information:

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

Best practice 11.1 – 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 the cost of storage and compute separately, and implement different cost optimization features to minimize cost.

Suggestion 11.1.1 – Use services that decouple compute from storage

Services that allow independent scaling of storage and compute allow for greater flexibility when handling workloads. This means when your workload is compute intensive you do not need to deploy a large storage array to meet the compute power for running your workload.

Suggestion 11.1.2 – Use Amazon Redshift RA3 instances types

Amazon Redshift RA3 instance types support the ability to decouple the compute and storage. This allows your Amazon Redshift storage to scale independently from your compute resources, which improves cost efficiencies for your data warehousing workloads.

Suggestion 11.1.3 – Use a decoupled file system for Big Data workloads

The EMR file system (EMRFS) is an implementation of HDFS that all Amazon EMR clusters use for reading and writing regular files from Amazon EMR directly to Amazon S3. By using EMRFS, your organization is only charged for the storage used, rather than paying for overprovisioned and underutilized HDFS EBS storage.

Suggestion 11.1.4 – 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. This reduces the overall amount of information that has been requested and reduces downstream data duplication.

Best practice 11.2 – 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 11.2.1 – 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 overprovisioning. An optimized EC2 instance runs your workloads with optimal performance and infrastructure cost. For example, choose the smaller instance if your growth ratio is low as this allows more granular incremental change.

Suggestion 11.2.2 – 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 that will result in lower costs.

Suggestion 11.2.3 – Use automatic scaling capability to meet the peak demand instead of over provisioning

Analytics services can scale dynamically to meet demand. Then, after the demand has dropped below a certain threshold, the service will remove the resources that are no longer needed. The automatic scaling of serverless services enables applications to handle sudden traffic spikes without capacity planning, reducing costs and improving availability.

There are a number of services that can automatically scale, and other services that you need to configure the scaling for. For example, AWS services like Amazon EMR, AWS Glue, and Amazon Kinesis can auto-scale seamlessly in response to usage spikes and remove resources without any configuration.

Best practice 11.3 – Use on-demand instances or serverless capacity for unpredictable workload usage

Serverless services typically only charge for the compute used, or the use of other measures like data processed, but only when there is a workload actively using the service. In contrast, allocating infrastructure yourself often means paying for idle resources.

Suggestion 11.3.1 – 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 11.3.2 – Use AWS Glue or Amazon EMR Serverless instead of Amazon EMR on EC2 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 on EC2 is typically used for frequently running jobs requiring semipersistent data storage.

Amazon EMR Serverless provides a highly cost-effective way to run EMR clusters and data pipelines on an infrequent or intermittent basis. Unlike provisioned clusters that incur hourly charges even when idle, Serverless allows you to spin up a cluster on-demand when a job is submitted, and tear it down automatically once the job completes. This means you only pay for the actual time the cluster is running to process your workload, optimizing costs for infrequent ETL, data processing, or when-necessary analysis jobs.

Suggestion 11.3.3 – Use serverless resources for unpredictable or spiky workloads

Use serverless analytics services, such as Amazon Redshift Serverless, Amazon EMR, Amazon Athena, Amazon QuickSight Serverless, and Amazon Managed Streaming for Apache Kafka (Amazon MSK) Serverless, to perform analytical queries, processing and streaming, with pay-as-you-go pricing. This helps remove the cost associated with idle resources.

You can also use serverless resources for development and testing needs.

For more details, see AWS serverless data analytics pipeline reference architecture.

Best practice 11.4 – Use auto scaling where appropriate

Auto scaling can be used to scale up and down resources based on workload demand. This often leads to cost reductions when applications can scale down during low demand, such as nights and weekends.

For more details, see SUS05-BP01 Use the minimum amount of hardware to meet your needs.

Suggestion 11.4.1 – Use Amazon Redshift elastic resize and concurrency scaling

If your data warehouse uses provisioned Amazon Redshift, you can use one of Amazon Redshift's many scaling options to ensure that your cluster is scaled, for example Elastic resize. You may also be able to size your cluster smaller and leverage concurrency scaling, a Redshift feature that automatically adds more compute capacity to your cluster as needed.

For more details, refer to the following information:

- Scale Amazon Redshift to meet high throughput query requirements
- Amazon Redshift: Elastic resize
- Amazon Redshift: Working with concurrency scaling

Suggestion 11.4.2 – Use Amazon EMR managed scaling

If you use provisioned Amazon EMR clusters for your data processing, you can use EMR managed scaling to automatically size cluster resources based on the workload for best performance. Amazon EMR managed scaling monitors key metrics, such as CPU and memory usage, and optimizes the cluster size for best resource utilization.

For more details, see Using managed scaling in Amazon EMR.

Suggestion 11.4.3 – Use auto scaling for ETL and streaming jobs in AWS Glue

Auto scaling for AWS Glue ETL and streaming jobs enables on-demand scaling up and scaling down of compute resources required for ETL jobs. This helps to allocate only the required computing resources needed, and prevents over- or under-provisioning of resources, which results in time and cost savings.

For more details, see Using auto scaling for AWS Glue.

Suggestion 11.4.4 – Use Application Auto Scaling to monitor and adjust workload capacity

Application Auto Scaling can be used to add scaling capabilities to meet application demand and scale down when the demand decreases. This can be used to scale Amazon EMR, Amazon Managed Streaming for Apache Kafka, and EC2 instances.

For more details, refer to the following information:

- Introducing Amazon EMR Managed Scaling – Automatically Resize Clusters to Lower Cost
- Adopt Recommendations and Monitor Predictive Scaling for Optimal Compute Capacity

12 – 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. Data analytics systems and the data

generated from them will grow over time into a mix of both shared and isolated-team resources. Your organization should establish a financial attribution model for these resources. Teams will understand how their use of data analytics influences costs to the business and this promotes a culture of accountability and frugality. Creating a financial accountability model will allow departments to cross-charge departments for shared resources.

ID	Priority	Best practice
☐ BP 12.1	Recommended	Measure data storage and processing costs per user of the workload.
☐ BP 12.2	Recommended	Balancing agility and skill sets - When to build local compared to centralized data analytics platforms.
☐ BP 12.3	Recommended	Build a common, shared processing system and measure the cost per analytics job.
☐ BP 12.3	Recommended	Restrict and record resource allocation permissions using AWS Identity and Access Management (IAM).

For more details, refer to the following information:

- 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 12.1 – Measure data storage and processing costs per user of the workload

Data analytics workloads have recurring stable costs and per-use costs, for example, a weekly reporting job with relatively static data storage fees or periodic unpredictable processing runtime fees. Your organization should establish a financial attribution mechanism that captures data

storage and workload usage when analytics systems are run. Using this approach, your end users (business unit, team, or individual) can be notified of their consumption at regular intervals.

Suggestion 12.1.1 – Use tagging or other attribution methods to identify workload and data storage ownership

Collaboration between business, IT, and finance team to agree on cost allocation, cost ownership, cost charging, and budget management. Create budget tracking policy for storage and workload using tagging. Agree on the governance approach to implement policy (that is, central and decentralize), billing allocation, charge back, and budget reporting.

For more details, refer to the following information:

- AWS Cloud Financial Management Blog: Cost Tagging and Reporting with AWS Organizations
- AWS Billing and Cost Management and Cost Management User Guide: Reporting your budget metrics with budget reports, Configuring AWS Budgets actions and Creating an Amazon SNS topic for budget notifications

Suggestion 12.1.2 – Implement cost-visibility and internal bill-back method to aggregate your teams' use of analytics resources

Notify teams of their analytics usage costs periodically. Build dashboards that provide teams visibility into how their work impacts costs to the business using a self-service approach.

You can view and optimize your costs through the AWS Cost and Usage Report and the Cost and Usage Dashboards Operations Solution (CUDOS) reports.

Best practice 12.2 – Build local or build centralized data analytics platforms

Teams can establish their own data analytics resources that support their analytical needs locally, rather than extracting information and transferring it to a central location. Decide when teams benefit from building local analytics resources, balancing required agility and team skillset with the need for a centralized analytics platform.

Suggestion 12.2.1 – Perform regular reviews of analytics operations to determine if the business can benefit from teams managing their own infrastructure

Teams may prefer to own and manage their own infrastructure, as this allows for more flexibility and agility in system design with fewer dependencies. Individual ownership also provides clear

cost visibility. In other cases, a shared processing system can be more efficient, where teams send data requests to a central provider. Tracking request volume by team enables cost attribution. A centralized team managing infrastructure benefits multiple groups through increased resource utilization and concentrated expertise. Centralized data repositories make enriching data simpler and provide a single access point. Organizations find centralized analytics helps meet compliance and governance needs.

In summary, there are trade-offs between decentralized team-owned infrastructure providing more flexibility compared to centralized shared infrastructure increasing utilization and governance. Teams and centralized providers can also coordinate, with centralized systems handling some processing and team systems providing customization. The best approach depends on the specific organizational needs and structure.

Best practice 12.3 – Restrict and record resource allocation permissions using AWS Identity and Access Management (IAM)

To better control costs, create distinct IAM roles that authorize users to provision certain resources. This ensures that only permitted individuals can provision the resources they are allowed to, preventing unauthorized and unnecessary spending.

Suggestion 12.3.1 – Create a cost governance framework that uses specialized IAM roles, rather than individual users, to provision costly infrastructure

Restrict the authorization to launch costly resources to specific IAM roles. For example, certain instances types can only be provisioned by certain teams to reduce unnecessary expenditure.

Suggestion 12.3.2 – Track AWS CloudTrail logs to determine overall usage-per-user and role

Track the usage across users and roles to get a clear understanding of resource usage. As part of your cost-allocation governance, automatically process the AWS CloudTrail logs so that cost allocation is properly attributed to the relevant department.

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. Implement a standardized process across your organization to identify and remove unused resources, such as unused data, infrastructure, and ETL jobs.

ID	Priority	Best practice
☐ BP 13.1	Recommended	Remove unused data and infrastructure.
☐ BP 13.2	Recommended	Reduce overprovisioning infrastructure.
☐ BP 13.3	Recommended	Evaluate and adopt new cost-effective solutions.

For more details, refer to the following information:

- AWS Database Blog: Safely reduce the cost of your unused Amazon DynamoDB tables using On-Demand mode.
- AWS Management and 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 – Remove unused data and infrastructure

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. This is 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. To reduce human effort, automate the data removal process. If data is stored in Amazon S3, use Amazon S3 Lifecycle configurations to expire data automatically.

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 that intermediate datasets are removed if they have no further business value.

Suggestion 13.1.4 – Remove 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.

Suggestion 13.1.5 – 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 is consumed or delivered. For example, in a sales analytics workload, it might not be necessary to perform analytics on each transaction as it arrives. In some cases, only hourly reports are needed by business management. Batch processing the transactions is more efficient and can reduce unnecessary infrastructure costs between batch processing jobs.

Suggestion 13.1.6 – Compress data to reduce cost

Data compression can significantly reduce storage and query costs. Columnar data formats like Apache Parquet stores data in columns rather than rows, allowing similar data to be stored contiguously. Using Parquet over CSV format can reduce storage costs significantly. Since services like Amazon Redshift Spectrum and Amazon Athena charge for bytes scanned, compressing data lowers the overall cost of using those services.

Best practice 13.2 – Continuously evaluate your provisioned resources and identify overprovisioned workloads

Workload resource utilization can change over time, especially with the growth of data or after process optimization has occurred. Your organization should review resource usage patterns and determine if you require the same infrastructure footprint to meet your business goals.

Suggestion 13.2.1 – Evaluate whether compute resources can be downsized

Investigate your resource utilization by inspecting the metrics provided by Amazon CloudWatch. Evaluate whether the resources can be downsized to one-level smaller within the same instance class. For example, reduce Amazon EMR cluster nodes from m5.16xlarge to m5.12xlarge, or the number of instances that make up the cluster.

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. From there, the data can be queried in place or joined with data in the warehouse. Use services such as Amazon 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, consider required access patterns, transaction concurrency, and acceptable transaction latency. These will influence where data is stored. It is equally important to consider how often data will be accessed. 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. These automatically transition objects into another tier with lower cost, and will even delete expired data. Amazon S3 Intelligent-Tiering will analyze the data access patterns and automatically move objects between tiers.

Suggestion 13.2.5 – Move to serverless when you don't need always-on infrastructure

For analytics workloads that have intermittent or unpredictable usage patterns, moving to AWS serverless can provide significant cost savings compared to provisioned servers. AWS serverless analytics services like Amazon Athena, EMR Serverless, and Amazon Redshift Serverless are great options that provide on-demand access without having to provision always-on resources. These services automatically start up when needed and shut down when not in use so you don't have to pay for idle capacity.

For example, with Amazon Redshift Serverless, you pay for compute only when the data warehouse is in use. By using Amazon Redshift Serverless for tasks such as loading data and leveraging Amazon Redshift data sharing, you can scale down your main cluster and still maintain the same performance for end users.

For more detail, refer to the following:

- Easy analytics and cost optimization with Amazon Redshift Serverless
- Amazon EMR Serverless cost estimator
- Run queries 3x faster with up to 70% cost savings on the latest Amazon Athena engine

Best practice 13.3 – 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 13.3.1 – 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 that Service Quotas are set high enough to cover the expected peak usage.

Suggestion 13.3.2 – 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 13.3.3 – Switch to a new service or take advantage of new features that can reduce cost

AWS consistently adds new capabilities to enable your organization to leverage the latest technologies to experiment and innovate more quickly. Your organization should review new service releases frequently to understand the price and performance, and determine if such features can improve cost reduction.

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. 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 Instance 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 information:

- 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 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.
- Amazon Redshift: Purchasing Amazon Redshift reserved nodes.

Best practice 14.1 – Evaluate the infrastructure usage patterns and choose your payment options accordingly

On-demand resources provide immense flexibility with pay-as-you-go payment models across multiple scenarios and scales. Alternately, Reserved Instances provide significant cost saving for workloads that have steady resource utilization and serverless options for unpredictable demand. 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 use.

Suggestion 14.1.2 – For steady, permanent workloads, obtain Reserved Instances or Savings Plans price discounts instead of paying On-Demand Instance pricing

Reserved Instances give you the option to reserve some AWS resources for a one- or a three-year term. In turn, you will receive a significant discount compared with 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 either on-demand, spot or serverless resources during development and in pre-production environments

Development and pre-production environments frequently change and often do not require 100% availability. Use on-demand instances with start and stop resources, or serverless resources in cases where workload utilization is unpredictable, frequently changes, or is only used for portions of the day. You can use spot instances for fault-tolerant and flexible big data analytics applications. Spot instances are available at up to a 90% discount compared to on-demand prices. Spot instances are not suitable for workloads that are inflexible, stateful, fault-intolerant, or tightly coupled between instance nodes.

For more detail, refer to the following:

- Optimize Cost by Automating the Start or Stop of Resources in Non-Production Environments Spot Instance Best Practices
- Optimizing Amazon EC2 Spot Instances with Spot Placement Scores

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 cost factors. These include the amount of capacity to reserve, the 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. This is because these options affect 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 Plan 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 your organization if they are unused in the account for which they are purchased.

Sustainability

Organizations and government departments play a critical role in conserving natural resources and protecting global ecosystems by reducing the use of materials, resources, and emissions.

The practice of designing and building sustainable cloud workloads requires understanding what environmental impact is attributable to your IT usage. You can then apply the best practices and suggestions in this section to reduce that impact.

Sustainability in the cloud is a continuous effort focused primarily on energy reduction and efficiency across all components of a workload. You can do this by achieving the maximum benefit from the resources provisioned and minimizing the total resources required. This effort can range from the initial selection of an efficient programming language, adoption of modern algorithms, use of efficient data storage techniques, deploying to correctly sized and efficient compute infrastructure, and minimizing requirements for high-powered end user hardware. Many of the best practices in the performance efficiency and cost optimization pillars also apply to building sustainable cloud workloads.

How do you ensure the services and the infrastructure deployed to ingest, process, and analyze data have been designed with sustainability as an architectural principle? This section details how to design your data platforms using architectural best practices to reduce the environmental impact of your organization's data analytics workloads.

Throughout this section, we explore various best practices to help understand how they can reduce the environmental impact of your analytics workloads. Implementing each of the best practices involves resource trade-offs. Your organization should examine these best practices, both holistically and individually, and agree on whether they are beneficial in meeting your sustainability goals. Data compression, for instance, minimizes your storage footprint. But, as a trade-off, more computing power is required to decompress the data. It is advised that your company tests the best practice recommendations to determine the level of storage compared to compute trade-offs and identify which approach is most sustainably beneficial.

Best practice

- 15 – Sustainability implementation guidance

15 – Sustainability implementation guidance

Think about sustainability as being a non-functional requirement when designing your systems. Determine how necessary sustainability best practices baked into your development lifecycle are, because sustainability best practice can be applied across all workloads, not just data and analytics.

ID	Priority	Best practice
BP 15.1	Recommended	Define your organization's current environmental impact
BP 15.2	Recommended	Encourage sustainable thinking
BP 15.3	Recommended	Encourage a culture of data minimization
BP 15.4	Recommended	Implement data retention processes to remove unnecessary data from your analytics environment
BP 15.5	Recommended	Optimize your data modeling and data storage for efficient data retrieval
BP 15.6	Recommended	Prevent unnecessary data movement between systems and applications
BP 15.7	Recommended	Efficiently manage your analytics infrastructure to reduce underutilized resources

Best practice 15.1 – Define your organization's current environmental impact

As an organization, you should track your progress towards your sustainability goals. By determining your current environmental impact, you can track and report improvements as you make changes over time. Without knowing where you are you can't know how far you've come.

How do you track your analytics carbon footprint?

Suggestion 15.1.1 – Determine the carbon emissions of your workload using the AWS Customer Carbon Footprint Tool

Determining the current carbon emissions of your analytics workloads at the start of your optimization journey is important as it enables you to track your changes and see what efforts have

the biggest impact. If you are an AWS user, your organization can use the AWS Customer Carbon Footprint Tool. The AWS Customer Carbon Footprint Tool is a data tracking and visualization tool that reports on your AWS accounts carbon usage.

Your organization should maintain an audit trail of the changes that your team have made, when they were made, and the impact that the changes had on the carbon footprint of each workload.

For more details, refer to the following information:

- AWS Customer Carbon Footprint Tool
- AWS Customer Carbon Footprint Tool Overview
- Sustainability Pillar Improvement Process
- Sustainability Pillar Improvement Process

Suggestion 15.1.2 – Define and track your progress using proxy metrics

When something is hard or impractical or very difficult to measure directly, you can instead use a related measurements in its place. This is called a *proxy metric*.

Environmental impact is hard to measure directly, especially when you want fine-grained measurements. However, in the cloud, the environmental impact of a workload is often correlated with efficiency, which is also often correlated with cost. Just like you can apply many of the best practices of the performance efficiency and cost optimization pillars to lower your environmental impact, you can also use performance metrics and cost as proxy metrics to track your progress.

For more details, refer to the following information:

- Evaluate specific improvements
- Turning Cost and Usage Reports into Efficiency Reports
- Best practice 8.3 – Define and measure the computing performance metrics

Best practice 15.2 – Encourage sustainable thinking

Software architects are often encouraged to apply systems thinking to the problems they tackle. To zoom out and look at the bigger picture and how the different components interact and form a whole. To build sustainable cloud workloads also requires sustainability thinking – including environmental impact as a parameter in design and planning.

Organizations should include sustainability requirements when considering new projects, and continuously evaluate the environmental impact of existing workloads. They should find the balance between business needs and sustainable goals – and creative solutions to achieve both.

Encourage questioning business requirements on sustainability grounds. For example, when considering the update frequency of dashboards, include the impact on things like energy usage in the discussions. Sometimes this leads to insights such as that only some of the KPIs need frequent updates, while the majority of the dashboard contents only need updating once per day. This can result in a reduction in energy usage while still delivering the same business value.

Suggestion 15.2.1 – Review the update frequency of your reports and dashboards

Running reports and refreshing dashboards can be a compute intensive process. Continuously review the business requirements and question how frequently refreshes are needed. Can some reports be run only on demand because they are accessed infrequently? Can reports that today run on demand instead be run on a schedule to have them always available instead of multiple people running them many times per day? Does every KPI need to be refreshed at the same time?

Suggestion 15.2.2 – Review your reports, dashboards, and metrics and remove what is no longer needed

As organizations evolve, so does business requirements.. Over time, some reports and dashboards become more important and used, and others less. New metrics become important, and reports and dashboards accumulate elements that are no longer necessary.

Continually evaluate business requirements and remove what is no longer needed. Remove metrics from reports when they are not necessary, and remove whole reports and dashboards when they lose their relevance. Efficient reporting has a positive impact on your sustainability goals. Your organization can also identify similar goals across teams or departments to reduce the number of separate reports and thereby reduce duplication and overlap.

Suggestion 15.2.3– Review the running frequency of your data pipelines

Data pipelines are the backbone of analytics platforms. They process data and produce new data sets. They are compute-intensive processes that can have a big impact on the overall environmental impact of your analytics platform. The more frequently they run, the higher the impact. Work backwards from your business requirements and decide appropriate running frequencies that balance business value and environmental impact.

Consider splitting pipeline jobs when there is an opportunity to run the majority of its calculations on a lower frequency while still maintaining the overall business goals.

Suggestion 15.2.4– Be flexible in your job schedules

It's common to run jobs on regular schedules, like hourly or daily, often at the top of the hour. When using managed and serverless technologies, the service often keeps a warm pool of compute resources to be able to meet demand. The pool needs to be managed to meet peaks in demand, and for job-oriented services this often coincides with the top of the hour. By being flexible in when you run your jobs, and for example avoiding the top of the hour, you can help the service smooth out demand.

This is similar to how you can optimize your own resource usage by implementing buffering and throttling, as described in SUS02-BP06 Implement buffering or throttling to flatten the demand curve.

Best practice 15.3 – Encourage a culture of data minimization

Analytics relies heavily on large volumes of data being stored and processed. Minimizing the amount of data stored and processed can have a positive impact on the environmental impact of your organization's analytics platform. Encourage architects, data engineers, and other roles that work on the platform to think about ways to minimize the amount of data stored and processed at every point in the system. A just enough data mindset can reduce the overall amount of data processed and therefore reduce the amount of compute power and storage used, and lower the environmental impact.

Look for opportunities to break linear relationships so that datasets don't need to grow at the same pace as your business. As your user base increases, find ways to avoid datasets growing at the same pace. In many cases it may be unavoidable, but for example, if you store partially aggregated data you can break the linear relationship.

Encouraging a culture of always thinking about ways to minimize data can help ensure your organization does not unintentionally increase its environmental impact again after reductions have been made. More information on building and implementing an Improvement process can be found in the Sustainability Pillar whitepaper.

How do you minimize the amount of data that is processed?

Suggestion 15.3.1– Minimize the amount of data extracted from your source systems that gets stored in your data warehouse

Data warehousing plays an important role in providing meaningful insights to your reporting layers and analytics. Data warehousing is the ingestion and merging of multiple data sources to create

a single data model optimized for the business' needs. Typically it employs techniques such as denormalization and materialized views of aggregates to provide faster query response times. It is encouraged that your organization applies these principles of building a data warehouse.

It is common that all source data is ingested into a data warehouse. Since data warehouses are good at storing massive amounts of data, and because it's hard to know in advance what is going to be needed, many organizations store everything. This leads to higher environmental impact because of the added compute and storage requirements.

Work backwards from the business needs, reports, and dashboards when designing ingestion processes and data models for data warehouses. This avoids the overhead of extracting, processing, and storing source data that is not strictly needed.

For more details, refer to the following information:

- Amazon Redshift development guide: Database Developer Guide
- Optimize your modern data architecture for sustainability: Part 1 – data ingestion and data lake

When designing your source data extraction processes, it is recommended that your organization should only extract data required for the workloads, such as reports and dashboards, that the data warehouse supports. This results in less data being transferred over the network, less data processed, less data being loaded into the data warehouse, less data being stored over time, and less data to remove when applying data retention policies.

When extracting data from your source datastore, your organization should use a date range to extract only data that has been added or updated in the source datastore since the last data extract. This is called delta updates. This approach reduces the environmental impact of reprocessing the same data multiple times.

Designing and building an efficient data model requires upfront consideration. Your development team should ensure that the optimal row-level granularity (for example customer level, address level, or product level) and data attributes reduces unnecessary deduplication and filtering further downstream.

Most reporting applications support data editing and data filtering capabilities. Therefore, your development teams can develop a subset of data within the business tool minimizing the amount of data required for a report refresh.

For more details, refer to the following information:

- Amazon QuickSight: Creating datasets

Suggestion 15.3.2 – Use appropriate data types when developing database tables

Databases and data warehouses can store many different types of data, and have optimized storage mechanisms for each type. Choosing the appropriate type for columns can optimize both the storage size of a dataset and the compute resources needed to process it. For example, storing numbers as integers, floats, and so on, instead of strings can save a lot of storage space, and greatly reduce the processing required when performing calculations. Similarly, dates and timestamps should be stored using matching data types. Consider each column and assign the most specific data type possible.

For more details, refer to the following information:

- Amazon Redshift best practices for designing tables
- Data types in Amazon Athena
- Amazon Redshift data types
- Amazon QuickSight: Supported data types and values

Suggestion 15.3.3 – Review your APIs to understand whether all data must be shared with your streaming applications

APIs play an important role in connecting and sharing data between applications, databases and other systems. Application developers should consider the size of an event payload submitted to these systems.

Organizations require the ability to run analytics on real-time data. To do so, organizations send data to streaming services. Streaming services, such as Amazon Managed Streaming for Apache Kafka (Amazon MSK) and Amazon Kinesis, allow organizations to run analytics on real-time streams of information. It is important that the data being shared with such streaming services is reviewed through the improvement process, because the more data provided in the payload will require more resources to store and process the data. Reducing the network, storage, and compute resources required to process unnecessary data can help towards reducing your organization's analytics environmental impact.

Review data that is captured by the application and pushed to the streaming platform to identify data attributes that can be removed. Also identify opportunities to store commonly used transforms to create values that can be computed once. Review your Kafka topic and identify if it's

duplicated data of whether a single topic is enough to deliver to multiple dependencies. Through the Improvement process you should consider data volumes and the value of your assets, and measure these against your organization's proxy metrics.

If it is not possible to reduce data at the point of data capture, as a developer, you can use AWS Lambda to trim event payloads of data attributes that are not required for downstream processing. However, as an organization, you should balance the trade-off of compute cost of removing the data versus retaining the original data values. This is not a binary option but should be measured over time to determine if it would be worthwhile removing data.

For more details, refer to the following information:

- AWS Lambda: Using AWS Lambda with Amazon Kinesis

Implement a monitor and alert strategy to get a clear picture of data growth over time. Take action on any significant data growth by understanding what additional attributes have been added to the event payload. Alerts should be implemented on thresholds, such as 3x data growth, or create an internal metric that your organization should expect to increase the overall data footprint aligned with new customers.

For more details, refer to the following information:

- Amazon Kinesis: Monitoring the Amazon Kinesis Data Streams Service with Amazon CloudWatch

Suggestion 15.3.4 – Reduce the amount of data migrated from one environment to another

Migrating data from one environment to another is a common exercise. Your organization should consider data minimization when migrating from one environment to another as migration requires additional network, storage, and compute resources for migrating unwanted information. Your organization should regularly review all information that is in scope of the migration and determine whether it is necessary for future workloads, rather than defaulting to a *migrate all* approach.

If your organization maintains a data catalog, a review of the data assets by a data owner prior to migrating the data should be performed to understand whether the data is required by the business.

For more details, refer to the following information:

- AWS Data Migration: Top 10 Data Migration

- AWS Data Migration (video): Top 10 Data Migration Best Practices

Suggestion 15.3.5 – Apply the optimal data model for your data access patterns

Understanding your data access patterns helps you determine which data modeling technique is most suitable. Work backwards from the way you access the data to determine the most suitable data model. There are two broad approaches to data modelling that you can start to consider: normalization and denormalization.

Normalization is the method of arranging the data in a data model to reduce redundant data and improve query efficiency. This method involves designing the tables and setting up relationships between those tables according to certain rules. Each piece of data is only stored once, and is referenced using its ID. Joins are used to reassemble the full data model. Typically, normalized data models are used in online transaction processing (OLTP) and are supported by relational databases that store the database data in rows. Normalized models minimize the amount of data stored, and compute power needed to make updates.

Denormalization is almost the opposite of normalization. Instead of referencing data using IDs, data is copied as many times as needed. Denormalized data models are typically used in online analytical processing (OLAP) where the data is stored in column-oriented massively parallel processing (MPP) databases such as Amazon Redshift. OLAP is designed for multidimensional analysis of data in a data warehouse, which contains both transactional and historical data. In MPP architectures data locality is important, and keeping redundant copies of data and avoiding joins can reduce the compute power needed, as well as network overhead. On the flip side, they may take up more storage, and updates require more compute power.

Whether you should choose normalization or denormalization for your data model depends on your data access patterns. Consider the way you query and update the data set first. In analytics, denormalized data models often perform better. The extra storage requirements from data duplication is often balanced by compression. When storing data in columns instead of rows, data encoding and compression becomes more efficient.

To normalize or denormalize is not an either-or proposition, but a scale. You can denormalize some parts of your data model heavily, while keeping other parts more normalized. For example, if you store personal data and have to be able to update and delete it easily, normalization of that part of the model may lead to the least environmental impact overall. Each query may become slightly less efficient, but you ensure you don’t have to rewrite the whole data set to remove multiple copies of a data point.

For more details, refer to the following information:

- Modern data architecture: Build a modern data architecture on AWS with Amazon AppFlow, AWS Lake Formation, and Amazon Redshift

Best practice 15.4 – Implement data retention processes to remove unnecessary data from your analytics environment

The retention of data should be informed, relevant, and limited to what is necessary for the purposes for which the data is processed. Storing data indefinitely and without purpose can cause significant storage and processing overhead that can impact your organization's analytics environmental impact. Ensure that the period for which the data should be stored is limited and reviewed on a regular basis.

How can you remove unnecessary data from an object store?

Suggestion 15.4.1 – Define and implement a data lifecycle process for data at rest

Implement a lifecycle management process that will either remove data that is no longer required, or archive data into less resource-intensive storage.

When removing data from an object store, your organization should consider the following design points:

- The data retention removal process should run on a regular basis
- The data retention removal process should remove data from all buckets, sub-directories and prefixes.
- The data retention removal process should take an audit of what data has been removed, when it was removed, and who performed the removal process. This audit data should be tracked in an immutable audit log for auditing purposes.
- Production, user acceptance test (UAT), and development (DEV) environments must be included and adhere to the agreed retention policy across all environments.
- Consider other locations where data might be stored, such as SFTP locations.
- Classify your organization's data by data temperature, such as *hot* for frequently accessed, and *cold* for infrequently accessed. After data has been classified by temperature, your organization should implement a strategy to move data into the respective S3 bucket storage classes. For example, cold data could be moved to Amazon S3 Glacier storage class. For an illustration of data temperatures, see Optimizing your AWS Infrastructure for Sustainability, Part II: Storage.

For more details, refer to the following information:

- Amazon S3 Lifecycle Management: Managing your storage lifecycle

How can you remove unnecessary data from databases?

Suggestion 15.4.2 – Remove unnecessary data from databases

To effectively remove information from a database, your organization should track when the data was loaded into the database and when the last customer interaction occurred, such as a purchase or other activity. This tracking helps you accurately identify when data should be removed.

- The data retention removal process should run frequently, but should not be run excessively, as excessive deletion can increase compute resources that could mitigate the benefit of removing the data from your database.
- The data retention removal process should remove data from all databases and tables.
- The data retention removal process should retain an audit of what data has been removed, when it was removed, and who performed the removal process. This audit data should be tracked in an immutable audit log for auditing purposes.
- If your database enforces referral integrity, you should redact only the data and retain the primary and foreign keys.

For more details, refer to the following information:

- Amazon Redshift: Amazon Redshift Stored Procedures
- Amazon Redshift: DELETE Statement
- Amazon Redshift: Scheduling a query on the Amazon Redshift console

Suggestion 15.4.3 – Use the shortest possible retention period in streaming applications

The primary use-case of a streaming application is to transfer information from source to target, but they can also retain data for a configured time. This allows replaying the stream to, for example, recover from corruption in a downstream system. At the same time, data stored in a streaming application becomes redundant as soon as it has been stored downstream. Determine the shortest possible retention period that you need to meet your Recovery Point Objective (RPO).

For more details, refer to the following information:

- Amazon Kinesis: Changing the Data Retention Period
- Amazon Managed Streaming for Apache Kafka: Adjust data retention parameters

Suggestion 15.4.4 – Design your application to make it possible to efficiently remove or archive outdated data

Designing a data model that supports efficient deletion of data can be surprisingly hard. In the worst case, the deletion of a single piece of data may require rewriting a large portion of the data set in a data lake. This is inefficient and has an unnecessary environmental impact. When designing an application, also design how you remove or archive data from it once that data is outdated, no longer relevant, or upon request.

Consider, and design for things like:

- How to delete all data belonging to a specific user
- How to delete data older than a specific time
- How to delete personal data

In data lakes and analytics applications it is often hard to delete individual pieces of data. Consider how to organize data to reduce the amount of data that has to be rewritten to delete a single piece of data – but always balance it against the impact to query performance.

It is often good practice to partition a data set in a data lake by time to make it possible to efficiently delete historical data when it is no longer needed. Similarly, in a data warehouse, keeping data sorted by time yields similar efficiencies.

For more details see:

- Optimize your modern data architecture for sustainability: Part 1 – data ingestion and data lake
- AWS Well-Architected Framework: SUS04-BP05 Remove unneeded or redundant data

Best practice 15.5 – Optimize your data modeling and data storage for efficient data retrieval

How your data is organized in a data store, database, or file system can have an impact on the amount of resources that are required to store, process, and analyze the data. Using encoding,

compression, indexes, partitioning, and similar tools we can make this more efficient and reduce the overall environmental impact of our analytics workloads.

How can your organization reduce the resources required to store, process, and analyze your organization's data in a sustainable manner?

Reducing data that a database system scans to return a result is an efficient way in reducing your organization's analytics environmental impact. This approach requires less resources to scan the disk to retrieve the information to service the request, and reduces the amount of provisioned storage required to service the workload. There are different methods that database engines use to optimize the amount of information scanned, such as partitioning, bucketing, and sorting.

Suggestion 15.5.1 – Implement an efficient partitioning strategy for your data lake

Partitioning plays a crucial role when optimizing data sets for Amazon Athena or Amazon Redshift Spectrum. By partitioning a data set, you can reduce the amount of data scanned by queries dramatically. This reduces the amount of compute power needed, and therefore the environmental impact.

When implementing a partitioning scheme for your data model, work backwards from your queries and identify the properties that would reduce the amount of data scanned the most. For example, it is common to partition data sets by date. Data sets tend to grow over time, and queries tend to look at specific windows of time, such as the last week, or last month.

For more details, refer to the following information:

- Amazon S3 and Amazon Athena: Partitioning and bucketing in Athena
- Amazon Athena: Partitioning data in Amazon Athena

Suggestion 15.5.2 – Configure and sort distribution keys on your Amazon Redshift tables

Amazon Redshift sort keys determine the order in which rows in a table are stored on the disk. When you query a data set in Redshift, it can leverage the sort order of the data to avoid reading blocks that are outside of the range of values you are looking for. By reading fewer blocks of data, this approach can result in a reduction of compute resources required.

For more details, refer to the following information:

- Amazon Redshift: Choose the best sort key

In Amazon Redshift, the distribution key, or distkey, determines how data is distributed between the nodes in a cluster. Choosing the right distribution keys can improve the performance of common analytical operations like joins and aggregations.

For more details, refer to the following information:

- Amazon Redshift: Automate your Amazon Redshift performance tuning with automatic table optimization
- Amazon Redshift: Distribution styles

Suggestion 15.5.3 – Enable results and query plan caching

Computing the same result over and over again is wasteful. Query engines and data warehouses often support result caching, and/or query plan caching. By enabling these you can reduce the overall amount of compute power needed for your analytics workload by eliminating recomputing results and/or query plans when the data set hasn't changed. This saves on compute resource and reduce the environmental impact.

For more details, refer to the following information:

- Amazon Redshift: Performance optimization
- Amazon Athena: Query result reuse

Suggestion 15.5.4 – Enable data compression to reduce storage resources

Your organization should consider compressing data in both object stores, such as Amazon S3, and if supported, in your organization's database systems. By compressing data, your organization is reducing the amount of storage and networking resources required for the workload. Database systems can decompress the data at a rate that is almost unnoticeable to the end user or application. As the data is compressed and then decompressed, this will also reduce the retrieval time of the database engine to fetch all the data from the storage array leading to a potential reduction in compute resources.

For more details, refer to the following information:

- **Amazon Redshift compression and encoding:** Amazon Redshift Engineering's Advanced Table Design Playbook: Compression Encodings
- **Amazon Redshift file compression parameter:** File compression parameters

- Amazon Redshift Compression: Compression encodings
- Amazon DynamoDB Compression: Using data compression
- Amazon Athena Compression Support: Amazon Athena compression support

Suggestion 15.5.5– Use file formats that optimize storage and compute needs

There are many different file formats that can be used to store data from the ubiquitous CSV format, through structured formats like JSON, and data lake-optimized formats like Parquet – each is designed to overcome specific technical challenges. There is no file format that meets all needs, and different formats have different uses.

For analytical workloads, columnar file formats like Parquet and ORC often perform better overall. They achieve higher compression rates, and help query engines scan less data. Through reduced storage and compute needs they can help reduce the environmental impact of your workload.

More information on how to choose the right format can be found in Choose the best-performing file format and partitioning.

Suggestion 15.5.6– Avoid using unnecessary operations in queries, use approximations where possible, and pre-compute commonly used aggregates and joins

Consider the computational requirements of the operations you use when writing queries. For example, think about how the result gets consumed. For example, avoid adding an ORDER BY clause unless the result strictly needs to be ordered.

Many compute-intensive operations can be replaced by approximations. Modern query engines and data warehouses, like Amazon Athena and Amazon Redshift, have functions that can calculate approximate distinct counts, approximate percentiles, and similar analytical functions. These often require much less compute power to run, which can lower the environmental impact of your analytical workload.

Consider pre-computing operations. When you notice that the complexity of your queries increase, or that many queries include the same joins, aggregates, or other compute intensive operations, this can be a sign that you should pre-compute these. Depending on your platform this can be in the form of adding steps to your data transformation pipeline, or by introducing a materialized view.

Best practice 15.6 – Prevent unnecessary data movement between systems and applications

Moving data around your organization can be very costly as it requires compute, networking, and storage resources. This can be particularly costly for analytics workloads as they generally require large quantities of information. When businesses move data around their organization, they increase the risk of creating duplicate data, which can impact your storage resource.

At the same time, making multiple copies of data can also reduce the overall amount of data transferred from each access to the data. When designing your data platform, consider the overall environmental impact and make informed choices about when and when not to duplicate data.

How does your organization mitigate the unnecessary data movement from one part of your organization to another?

Suggestion 15.6.1 – Implement data virtualization techniques to query information where the data resides

In data virtualization, only the data that is required to service the request is copied from the source location into the data virtualization layer and temporarily cached in memory. This data is then used to service the user's request. By copying the most frequently used parts of the data set closer to the compute instances, overhead associated with data movement is reduced, and the query processing has more efficient access to the data.

For more details, refer to the following information:

- Use Amazon Athena for data virtualization: Amazon Athena
- Running Presto and Trino on Amazon EMR: Presto and Trino

Suggestion 15.6.2 – Reduce the flow of data between application and database by implementing predicates pushdown

Filtering data by pushing down predicates as close to the storage as possible reduces the amount of data that upstream systems need to process. Query engines like Amazon Athena have query planners that leverage predicate pushdown where possible. For example, when using columnar file formats like Parquet and ORC, Athena can use metadata stored in the files to determine which sections of the files to read, effectively pushing down some predicates to the storage layer. Similarly, when querying a federated data source, Athena can push down some, but not all, predicates into the source systems. This reduces the amount of data that needs to be transferred from the source system into the query engine itself. Research the query engine you use to determine under which circumstances it is able to perform predicate pushdown, and leverage this in your application.

For more details, refer to the following information:

- Use pushdown predicated with Amazon Athena: Top 10 Performance Tuning Tips for Amazon Athena
- Optimizing EMR Spark with leveraging pushdown predicates: Optimize Spark performance

Suggestion 15.6.3 – Prevent data movement by leveraging pre-calculated materialized views

A materialized view can reduce the amount of data shared between your data warehouse and reporting layers by pre-computing the results of a pre-defined query. Materialized views are especially useful for speeding up queries that are predictable and repeated. Instead of performing resource-intensive queries against large tables (such as aggregates or multiple joins), applications can query a materialized view and retrieve a precomputed result set, therefore, saving on compute resource and reducing an organization's analytics environmental impact.

Where materialized views are not available, you can use operations such as CREATE TABLE AS (CTAS) to create pre-computed versions of queries.

For more details, refer to the following information:

- Amazon Redshift: Creating materialized views in Amazon Redshift
- Amazon Athena: Creating a table from query results (CTAS)

Suggestion 15.6.4 – Reduce the flow of data between an operational database and a data warehouse by using federated querying

A federated query allows you to directly query data stored in external databases without data movement. This allows data analysts, engineers, and data scientists to perform SQL queries across data stored in relational, non-relational, object, and custom data sources. With federated querying, you can submit a single SQL query and analyze data from multiple sources running on premises or hosted in the cloud, which reduces data latency in reporting. Federated querying can reduce the amount of information shared between data stores, however, the sustainability trade-off is that your organization could transfer the same information multiple times rather than a once-off single bulk copy of all information on a daily basis. Your organization should frequently review your federated querying patterns to identify whether it's more sustainable to use federated query or single bulk copies. To do this, your organization could review the amount of data that has been queried in a week, versus calculating the size of a full extract, and implement the approach that processes the least amount of data.

For more details, refer to the following information:

- Amazon Redshift: Querying data with federated queries in Amazon Redshift
- Amazon Athena: Using Amazon Athena Federated Query

Suggestion 15.6.5 – Decrease the amount of data duplication between Amazon Redshift clusters by using data sharing

Data sharing allows an administrator to share databases, tables, and views from one Amazon Redshift cluster to another cluster without copying the underlying data. The consumer cluster can query live data, meaning changes made on the producer cluster reflect immediately on the consumer cluster. This removes the need to create, store, and keep copies of data sets up-to-date.

For more details, refer to the following information:

- Amazon Redshift: Amazon Redshift Data Sharing

Best practice 15.7 – Efficiently manage your analytics infrastructure to reduce underutilized resources

Ensuring your organization has the correct amount of resource provisioned for your workload is a difficult and challenging task. The common approach for ensuring your organization has the sufficient number of resources available for unpredicted peaks is to overprovision your resources. However, this approach generally leads to underutilization, and energy waste.

When designing your analytics workloads, consider using managed and serverless services. Managed services shift responsibility for maintaining high average utilization, and sustainability optimization of the deployed hardware, to AWS. Use managed services to distribute the sustainability impact of the service across all tenants of the service, reducing your individual contribution.

For a wider understanding of optimizing infrastructure for sustainability, refer to the following information:

- Well-Architected Sustainability: Optimizing your AWS Infrastructure for Sustainability, Part I: Compute
- Well-Architected Sustainability: Optimizing your AWS Infrastructure for Sustainability, Part II: Storage

How does your organization ensure efficient infrastructure usage?

Suggestion 15.7.1– Use managed and serverless services

Serverless is ideal when it is difficult to predict compute needs, such as with variable workloads, periodic workloads with idle time, and steady-state workloads with spikes. These kinds of workloads are common in analytics applications. Data processing pipelines, running reports, and as-necessary queries are some examples.

Use serverless services AWS Glue ETL and Amazon EMR Serverless to run your data processing jobs and let AWS manage and optimize the underlying resources efficiently. Similarly, using Amazon Athena and Amazon Redshift Serverless for data lakes and data warehousing ensures that you only use compute resources when needed, and allow these services to optimize resource utilization behind the scenes.

For more details, refer to the following information:

- Amazon Athena
- AWS Glue
- Amazon Redshift Serverless
- Amazon EMR Serverless

Suggestion 15.7.2– Pause your data warehouse and compute clusters when not in use

Compute resources should only be allocated when needed. If your workload cannot leverage serverless technologies, you should implement a process of stopping your compute clusters if there are periods when they will not be used (for example, during nights and weekends).

If your data warehouse uses Amazon Redshift, you can use the pause and resume feature. This retains the underlying data structures so that you can resume the cluster when needed. You can pause and resume clusters using the console, or the API, or even create a schedule that automatically pauses and resumes the cluster at set times.

Pausing data warehouse and compute clusters when not in use ensures there are fewer underutilized resources and reduces the environmental impact of your analytics workload.

For more details, refer to the following information:

- Amazon Redshift pause and resume: Lower your costs with the new pause and resume actions on Amazon Redshift

- Amazon Redshift pause and resume: Pausing and resuming clusters
- AWS Well-Architected Framework Data Analytics: Decouple storage from compute

Suggestion 15.7.3 – Scale your data warehouses and compute clusters to match demand

Only the necessary amount of compute resources should be allocated at any time. Scaling your data warehouse and compute clusters to match demand helps you maximize resource utilization, and reduce the environmental impact of your analytics workload.

For more details, refer to the following information:

- AWS Well-Architected Framework: SUS05-BP01 Use the minimum amount of hardware to meet your needs
- AWS Well-Architected Framework Data Analytics: Best practice 11.4 – Use auto scaling where appropriate
- Scale Amazon Redshift to meet high throughput query requirements
- Amazon Redshift: Elastic resize
- Amazon Redshift: Working with concurrency scaling

Suggestion 15.7.4 – Run your analytics workloads on spare capacity in your Amazon EKS environment for optimal application infrastructure usage

If you use Amazon EKS to run your applications, you can use Amazon EMR on Amazon EKS to also run your analytics workloads, such as Apache Spark jobs, on the same infrastructure. This can make it possible to increase the utilization of your existing compute resources.

For more details, refer to the following information:

- Amazon EMR on Amazon EKS

Resources

Documentation and blogs

- AWS Customer Carbon Footprint: AWS Customer Carbon Footprint Tool
- Amazon QuickSight: Creating datasets
- Amazon Athena data types: Data types in Amazon Athena

- Amazon Redshift data types: Data types
- Amazon QuickSight: Supported data types and values
- Amazon QuickSight: Using AWS Lambda with Amazon Kinesis
- Amazon Kinesis: Monitoring the Amazon Kinesis Data Streams Service with Amazon CloudWatch
- AWS Data Migration: Top 10 Data Migration
- Amazon S3 Lifecycle Management: Managing your storage lifecycle
- Amazon Kinesis: Changing the Data Retention Period
- AWS-Managed Service Kafka: Adjust data retention parameters
- Amazon S3 and Amazon Athena: Partitioning and bucketing in Athena
- Amazon Athena: Partitioning data in Amazon Athena
- Amazon Redshift development guide: Database Developer Guide
- Amazon Redshift: Amazon Redshift Stored Procedures
- Amazon Redshift: DELETE Statement
- Amazon Redshift: Ingesting and querying semi-structured data in Amazon Redshift
- Amazon Redshift data types: Data types
- Amazon Redshift: Scheduling a query on the Amazon Redshift console
- Amazon Redshift: Choose the best sort key
- Amazon Redshift Serverless: Amazon Redshift Serverless
- Amazon Redshift: Automate your Amazon Redshift performance tuning with automatic table optimization
- Amazon Redshift: Distribution styles
- Amazon Redshift: Performance optimization
- Amazon Redshift best practices: Amazon Redshift best practices for designing tables
- Amazon Redshift: Getting started with Amazon Redshift Spectrum
- Amazon Redshift: Querying external data using Amazon Redshift Spectrum
- Amazon Redshift file compression parameter: File compression parameters
- Amazon Redshift Compression: Compression encodings
- Amazon Redshift: Creating materialized views in Amazon Redshift
- Amazon Redshift: Querying data with federated queries in Amazon Redshift
- Amazon Redshift compression and encoding: Amazon Redshift Engineering's Advanced Table Design Playbook: Compression Encodings

- Modern data architecture: Build a modern data architecture on AWS with Amazon AppFlow, AWS Lake Formation, and Amazon Redshift
- Amazon DynamoDB Compression: Using data compression
- Amazon Athena Compression Support: Amazon Athena compression support
- Use Amazon Athena for data virtualization: Amazon Athena
- Running Presto and Trino on Amazon EMR: Presto and Trino
- Use pushdown predicated with Amazon Athena: Top 10 Performance Tuning Tips for Amazon Athena
- Optimizing EMR Spark with leveraging pushdown predicates: Optimize Spark performance
- Amazon Athena: Using Amazon Athena Federated Query
- EMR-Managed Scaling: Using EMR-Managed scaling in Amazon EMR
- EMR-Managed Scaling: Introducing Amazon EMR-Managed Scaling – Automatically Resize Clusters to Lower Cost
- Amazon EMR: EMR File System (EMRFS)
- Amazon Redshift cluster scaling: How do I resize an Amazon Redshift cluster?
- Amazon EMR on EKS: Amazon EMR on Amazon EKS
- Amazon EMR: Launch a Spark job in a transient EMR cluster using a Lambda function
-

Whitepapers

- Well-Architected Sustainability: Optimizing your AWS Infrastructure for Sustainability, Part I: Compute
- Well-Architected Sustainability: Optimizing your AWS Infrastructure for Sustainability, Part II: Storage

Demonstrations

- AWS Customer Carbon Footprint overview: AWS Customer Carbon Footprint Tool Overview
- AWS Data Migration (video): Top 10 Data Migration Best Practices

Scenarios

In this section, we cover the seven key scenarios that are common in many analytics applications. We describe 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

Data discovery

Many organizations treat data like an organizational asset, meaning it is no longer the property of individual departments. You want to analyze all types of data to drive actionable insights, be prepared for the unexpected, create new revenue streams, improve customer experience, and increase operational efficiencies.

The data discovery process consists of a number of interactive sessions with various stakeholders within an organization. Sometimes this starts with an initial session to identify new ways to extract value from your data, while at other times, it could be with a specific use-case around what you want to do. You can go straight into identifying key people and diving deep to gather the information that is need in order to determine your best possible solution.

In either case, the end goal is to maximize the value you get from the data and identify appropriate next steps. This includes how you plan to consume data, what data sources you have and how to ingest that data, and then potentially what types of transformations you may need for the data.

Characteristics

The common issue that can hold you back from maximizing the value of your data is the variety of data silos within your organization. Silos can prevent you from extracting maximum value from all your data with the greatest flexibility. Data warehouses can help with this to a point, but often only a small portion of raw data is bought into the data warehouse. Organizations often end up with multiple data warehouses, so you can still have these silos. There are a number of modern approaches to enterprise-wide analytics that can help solve this – such as data lakes, modern data architectures, and data mesh. If you are not already exploring these modern approaches, this is a good opportunity to learn more about these architectures in the following sections.

Another common issue is whether you can benefit from increasing the velocity at which you ingest and process your data. Many organizations still have a predominantly batch-oriented strategy to processing the data, where a majority of your data is processed on a daily schedule. You can ask yourself questions such as 'How can we benefit if we have access to more up-to-date data?" AWS can help you explore options for ingesting streaming data, and for processing data in micro-batches or employ stream processing.

If you have previously explored streaming options in the past, you might have been concerned about the complexity of some of these solutions, but there are many AWS-managed solutions for streaming that significantly reduces much of this complexity.

In general, data discovery consists of five steps:

1. Define the business value

This is the first step in data discovery where you define the business value or opportunity by conducting interactive sessions. Here are a few example questions to define the business opportunity.

- What insights are you getting from the data?
- How would getting insight into data provide value to the business?
- Are you looking to create a new revenue stream from your data?
- What are challenges with your current approach and tool?
- What are you not providing to your customers that you would like to provide?
- Who is the executive level stakeholder for this effort?
- Example-specific use case questions:

- How does data define your customer acquisition strategy?
- Would your business benefit from exploring modern approaches to managing fraud detection, predictive maintenance, customer 360, IoT, clickstream, operational analytics, root-cause analysis to reduce mean time to detection and mean time to recovery?
- How are you continually innovating on behalf of your customers and improving their user experience?

2. Identify your user personas

In this step, you focus on your data consumers, such as business analysts, data engineers, data analysts, and data scientists. Once you have developed your user personas, enable them for purpose-built analytics and machine learning.

Here are few example questions to identify your data consumers.

- Who are the end users?
- What insights are you currently getting from your data?
- What insights are on your roadmap?
- Do you have a multi-tenant data model?
- What are the different consumption models?
  - Which tool or interface do your data consumers use?
  - How real time does the data need to be for this use case (for example, near real time, every 15 minutes, hourly, daily)?
  - What is the total number of consumers for this consumption model?
  - What is the peak concurrency?

3. Identify your data sources

In this step, you focus on your data sources and tools to bring that data into the data platform. This allows you to perform comprehensive analytics and machine learning from a wide variety of data from various data sources.

Data types and sources

Table 3: Typical data sources in an organization

Data type	Example data sources	
Structured data	ERP applications, CRM applications, ERP applications, CMS applications, SaaS applications, SAP applications, line of business (LOB) applications, and SQL databases	
Semi-structured data	Web applications, NoSQL databases, EDI (electronic data interchange), CSV, XML, and JSON documents	
Unstructured data	Video files, audio files, images, IoT data, sensors data, and invoices	
Batch	Internal applications generate structured data at regularly defined schedules	
Streaming data	Sensors, social media, video streams, IoT devices, mobile devices that generate semi-structured and unstructured data as continuous streams	

Here are a few example questions to identify your data consumers.

- How many data sources do you have to support?
  - Where and how is the data generated?
  - What are the different types of your data? (for example, structured, semi-structured, unstructured, batch, streaming)
  - What are the different formats of your data? (for example, JSON, CSV, FHIR)

  - Is your data originating from on premises, a third-party vendor, or the cloud?
  - Is the data source streaming, batch, or micro-batch?
  - What is the rate and volume of ingestion?
  - What is the ingestion interface (for example, API, SFTP, Amazon S3, AWS Marketplace)
- How does your team on-board new data sources?

4. Define your data storage, catalog, and data access needs

In this step, you focus on your data storage, data cataloging, security, compliance, and data access requirements.

Here are few example questions to identify your data storage and data access requirements.

- What data stores do you have?
- What is the purpose of each data store?
- Why that storage method? (for example, files, SQL, NoSQL, data warehouse)
- How do you currently organize your data? (for example, data tiering, partition)
- How much data are you storing now, and how much do you expect to be storing in the future, for example, 18 months from now?
- How do you manage data governance?
- What data regulatory and governance compliance do you face?
- What is your disaster recovery (DR) strategy?

5. Define your data processing requirements

In this step, you focus on your data processing requirements.

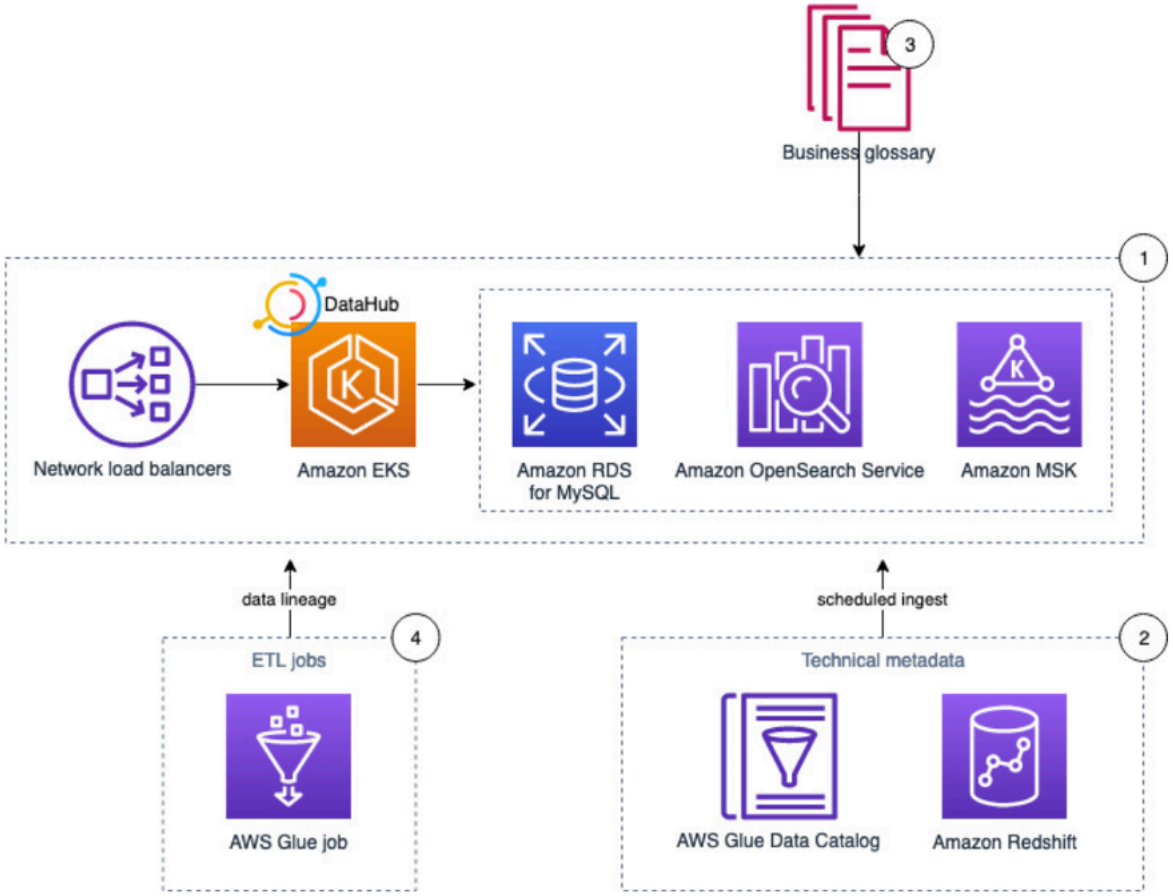
Here are few example questions to identify your data processing requirements.

- Do you have to transform or enrich the data before you consume it?
- What tools do you use for transforming your data?
- Do you have a visual editor for the transformation code?
- What is your frequency of data transformation? (for example, real time, micro-batching, overnight batch)

- Are there any constraints with your current tool of choice?

Reference architecture

The following diagram illustrates the solution architecture and its key components for data cataloging, security, compliance, and data access requirements using DataHub.



Reference architecture for data discovery

1. DataHub is an open-source metadata management platform which enables end-to-end discovery, data observability, data governance , data lineage and many more. It runs on an Amazon EKS cluster, using Amazon OpenSearch Service, Amazon Managed Streaming for Apache Kafka (Amazon MSK), and RDS for MySQL as the storage layer for the underlying data model and indexes.
2. Pull technical metadata from AWS Glue and Amazon Redshift to DataHub.
3. Enrich the technical metadata with a business glossary.

4. Run an AWS Glue job to transform the data and observe the data lineage in DataHub.

Modern data architecture

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 also common for these organizations to 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 analyze all of the data that is spread across the data lake and other data stores efficiently, businesses often move data in and out of the data lake and between these data stores. This data movement can get complex and messy as the data grows in these data stores.

To address this, businesses need a data architecture that allows building scalable, cost-effective data lakes. The architecture can also support simplified governance and data movement between various data stores. We refer to this as a *modern data architecture*. Modern data architecture 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 modern data architecture, organizations can store their data in a data lake and use purpose-built data stores that work with the data lake. This approach allows access to all of the data to make better decisions with agility.

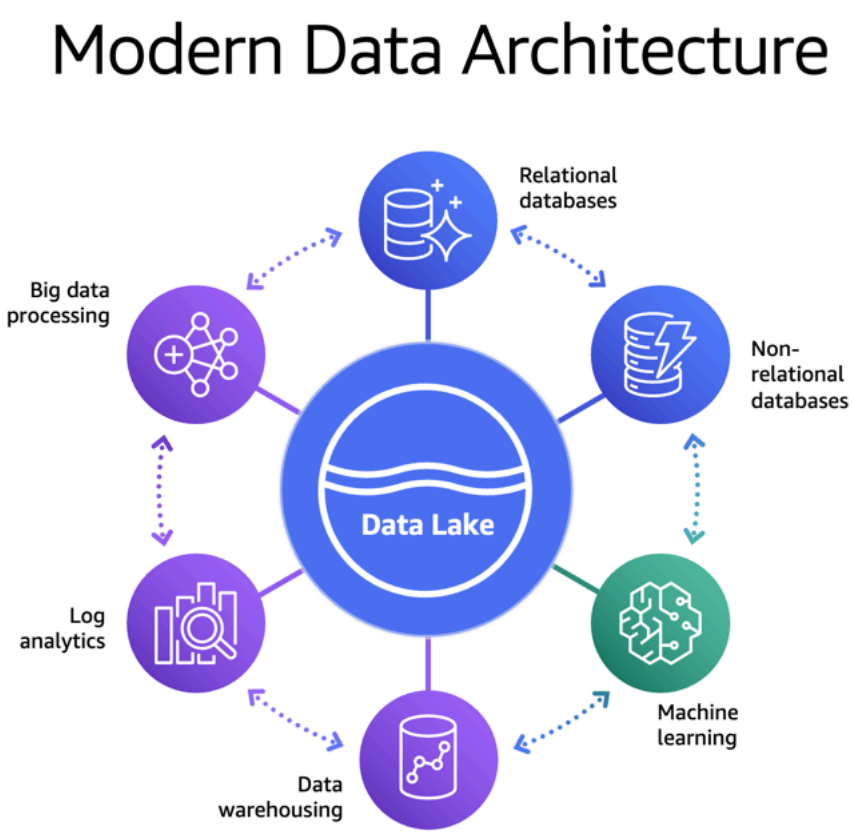


Figure 1: Modern data architecture

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. This pattern supports specialized analytics, such as search analytics, building knowledge graphs, or both. For example, enterprises send information from structured sources (such as relational databases), unstructured sources (such as metadata, media, or spreadsheets) and other assets to a data lake. From there, it is moved to Amazon Neptune to build a knowledge graph. We refer to this kind of data movement as inside-out.

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 example, to maintain game state, player data, session history, and leader boards, a gaming company might choose 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 their players. We refer to this kind of data movement as outside-in.

Around the perimeter: In addition to the two preceding 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. We refer to this kind of data movement as around the perimeter.

Characteristics

Scalable data lake: 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 modern data architecture 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 that 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 queryable interface for all data assets is recommended.

Unified governance: A modern data architecture 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 overly complex and error prone. Having a centralized location to define the policies and enforce them is critical to a secure modern data 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.

Transactional Data Lake: Data lakes offer one of the best options for cost, scalability, and flexibility to store data at a low cost, and to use this data for different types of analytics workloads. However, data lakes are not databases, and object storage does not provide support for ACID processing semantics, which you may require to effectively optimize and manage your data at scale across hundreds or thousands of users using a multitude of different technologies. Open

table formats provide additional database-like functionality that simplifies the optimization and management overhead of data lakes, while still supporting storage on cost-effective systems. These features include:

- **ACID transactions:** Allowing a write to completely succeed or be rolled back in its entirety
- **Record-level operations:** Allowing for single rows to be inserted, updated, or deleted
- **Indexes:** Improving performance in addition to data lake techniques like partitioning
- **Concurrency control:** Allowing for multiple processes to read and write the same data at the same time
- **Schema evolution:** Allowing for collumns of a table to be added or modified over the life of a table
- **Time travel:** Query data as of a point in time in the past

The three most common and prevalent open table formats are Apache Hudi, Apache Iceberg, and Delta Lake.

Reference architecture

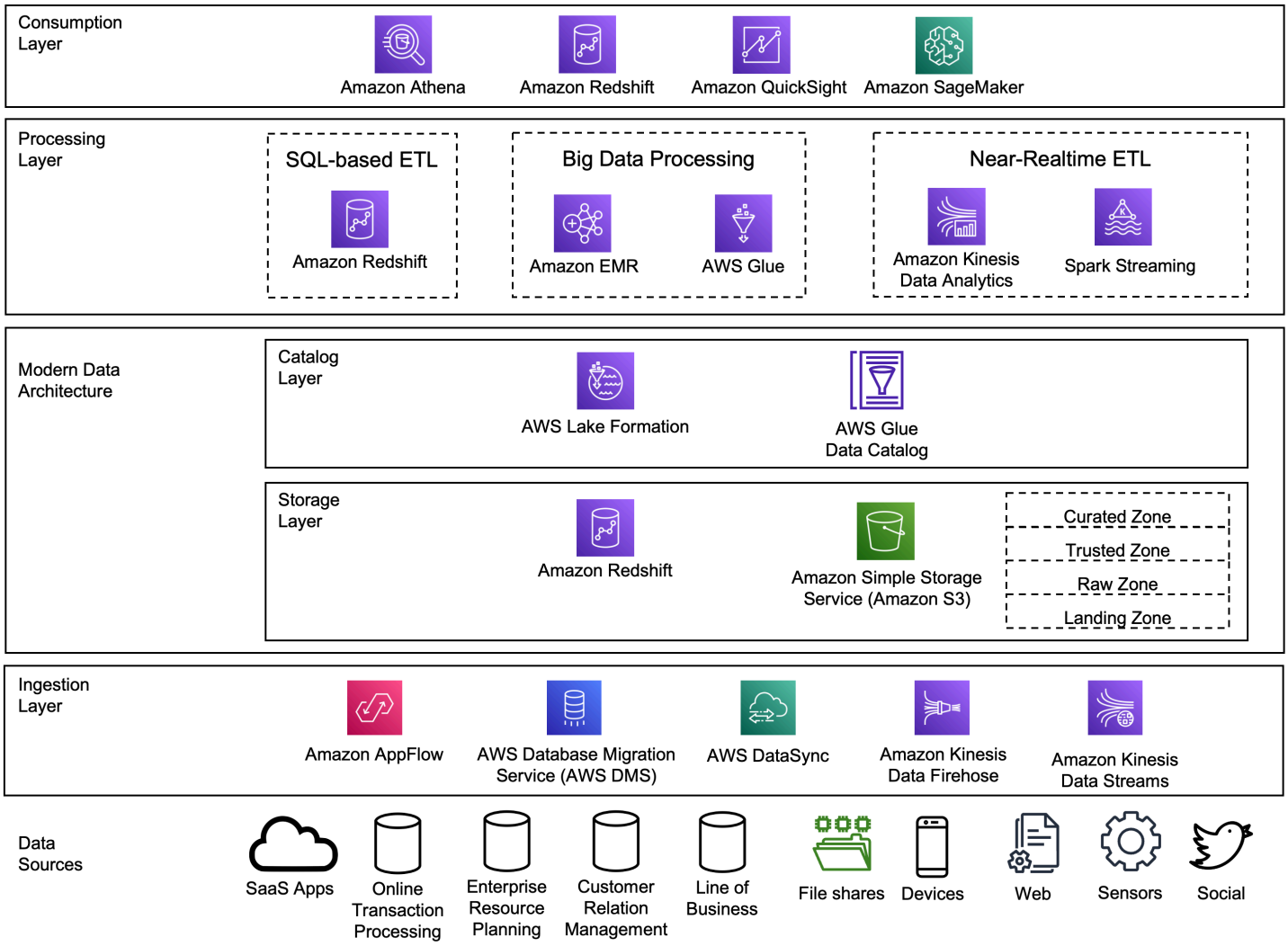


Figure 2: Modern data architecture reference architecture

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 delete old data automatically to meet your data retention requirements.
- Decide on a location for data lake ingestion, for example, an S3 bucket. Select a frequency and isolation mechanism that meet your business needs.
- Depending on your ingestion frequency and 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.
- There is 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 details, refer to the Derive Insights from AWS Modern Data whitepaper.

User personas

To get the full value from your modern data architecture, there are various personas who will access the data and perform data analytics. For example, the chief data officer (CDO) of an organization is responsible for driving digital innovation and transformation across lines of business. This CDO should set a data-driven vision for the organization and be a champion of using data, analytics, and AI/ML to inform business decisions.

Table 4: Key personas for a modern data architecture

Personas	Responsibility	Areas of interest	Modern data architecture purpose-built AWS services
Chief data officer (CDO)	Build a culture of using data to	Data quality, data governance, data and AI strategy, evangeliz	AWS Lake Formation, Amazon OpenSearch Service

	solve problems and accelerate innovation.	e the value of data to the business.	
Data architect	Driven to architect technical solutions to meet business needs. Focuses on solving complex data challenges to help the CDO deliver on their vision.	Data pipeline, data processing, data integration, data governance, and data catalogs.	AWS Glue, Amazon EMR, Amazon Redshift, Amazon Athena, Amazon OpenSearch Service
Data engineer	Deliver usable, accurate dataset to organization in a secure and performant manner.	Variety of tools to build data pipeline, ease of use, configura tion, and maintenan ce.	AWS Glue, Amazon EMR, Amazon Kinesis, Amazon Redshift, Amazon Athena, Amazon OpenSearch Service
Data security officer	Data security, privacy, and governance must be strictly defined and adhered to.	Keeping information secure. Comply with data privacy regulatio ns and protecting personally identifia ble information (PII), applying fine-grained access controls and data masking.	AWS Lake Formation , AWS Identity and Access Management (IAM).
Data scientist	Construct the means for extractin g business-focused insight from data quickly for the business to make better decision.	Tools that simplify data manipulation, and provide deeper insight than visualiza tion tools. Tools that help build the ML pipeline.	Amazon SageMaker, Amazon Athena, Amazon QuickSight, AWS Glue Studio, AWS Glue DataBrew

Data analyst	React to market conditions in real time, must have the ability to find data and perform analytics quickly and easily.	Querying data and performing analysis to create new business insights, producing reports and visualizations that explain the business insights.	Amazon Athena, Amazon QuickSight, AWS Glue Studio, Amazon Redshift

Batch data processing

Most analytics applications require frequent batch processing that allows them to process data in batches at varying intervals. 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 to scale seamlessly to the size of the dataset being processed by various job runs.

It is important for the batch processing system to be able to support disparate source and target systems. These include processing various data formats, seamlessly scaling out to process peak data volumes, orchestrating jobs using workflow, providing a simple way to monitor the jobs, and most importantly offering 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, and AWS Glue DataBrew allow you to run batch data processing jobs at scale for all batch data processing use cases and for various personas. These personas include data engineers, data analysts, and data scientists. While there are some overlapping capabilities between these services, knowing the core competencies and when to use which service or services allows 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 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 much 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. This helps them normalize and clean data up to 80% faster compared to traditional approaches to data preparation.

Support disparate source and target systems: Your batch processing system should support 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, and 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 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 help you identify errors and tuning opportunities quickly 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 pay only 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

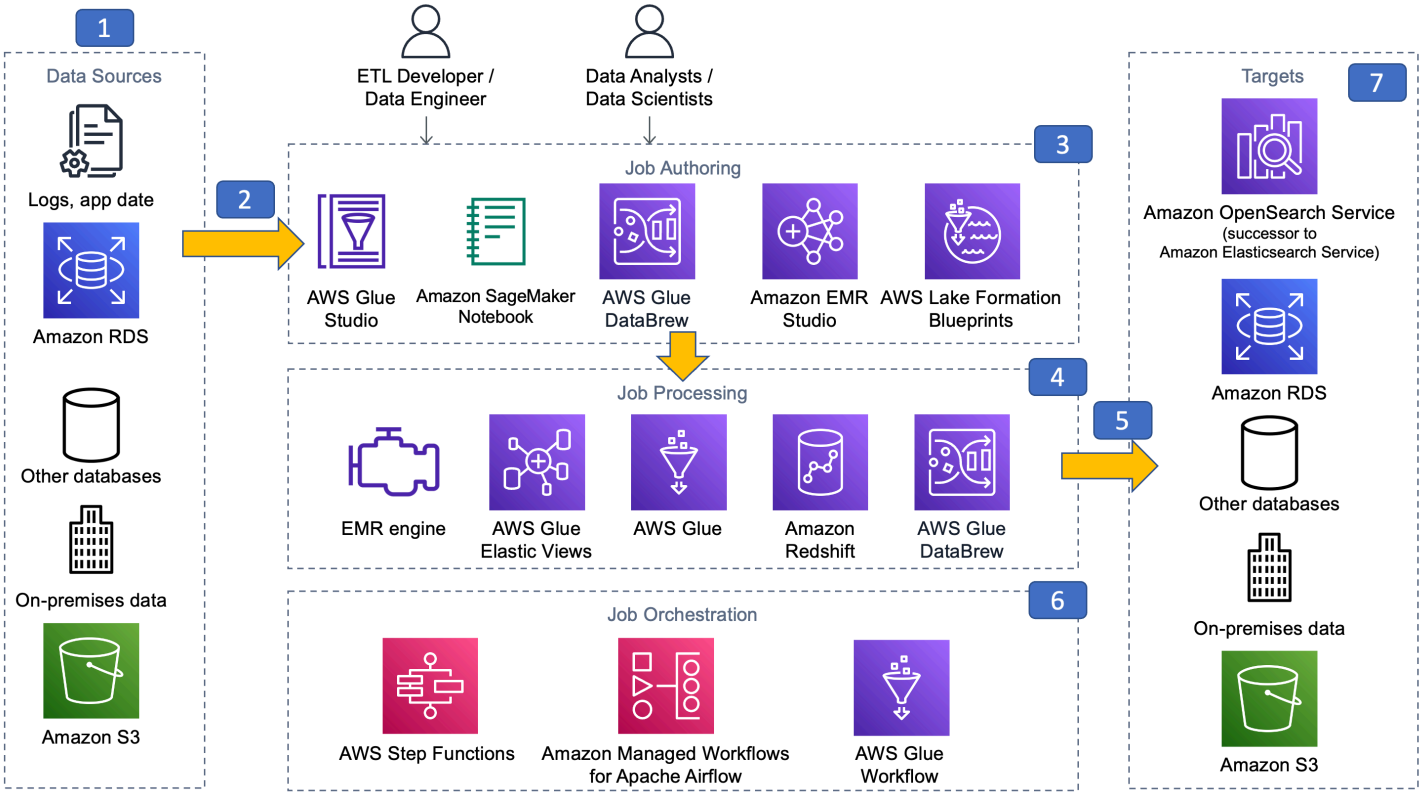


Figure 3: Batch data processing reference architecture

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 in 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 also can 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 or Glue interactive sessions when authoring jobs for the AWS Glue Spark runtime engine.

b. Use AWS Glue blueprints when you create a self-service parametrized job for analysts and control what data the analyst is allowed to access.

c. Use Amazon EMR notebooks for interactive job development and scheduling notebook jobs against Amazon EMR.

d. Use Amazon SageMaker notebook when working within SageMaker development and pre-processing data using Spark on EMR.

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 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. Amazon EMR, AWS Glue (Streaming) ETL and Amazon Redshift offer the ability to scale seamlessly based on your job runtime metrics using managed scaling, automatic scaling, and concurrency scaling features for read and write, respectively. Amazon EMR and Amazon Redshift offer both server-based and serverless architectures while the other services depicted in the reference architecture are fully serverless. Amazon EMR (server-based) 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 environments, 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. AWS Glue jobs also support a bookmarking capability that keeps track of what it has processed and what will be processed during next run. Similarly, AWS Lake Formation blueprints support a bookmarking capability when processing incremental data. With Amazon 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 (Amazon MWAA) that allows you to interoperate between any service including external dependencies.

7. Batch processing jobs write data output to a target data store, which can be anywhere in the AWS Cloud, on premises, or at another cloud provider. You can use the AWS 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 analytics 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 overprovisioned resources on Amazon EC2. For example, traditional Hadoop clusters are often overprovisioned 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 modern data architecture 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 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, Managed Service for Apache Flink 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 (Amazon MSK) 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: 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 can choose a message delivery system that supports one or more of these required semantics.

Security: Streaming ingest and processing systems must be secure by default. You must 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 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

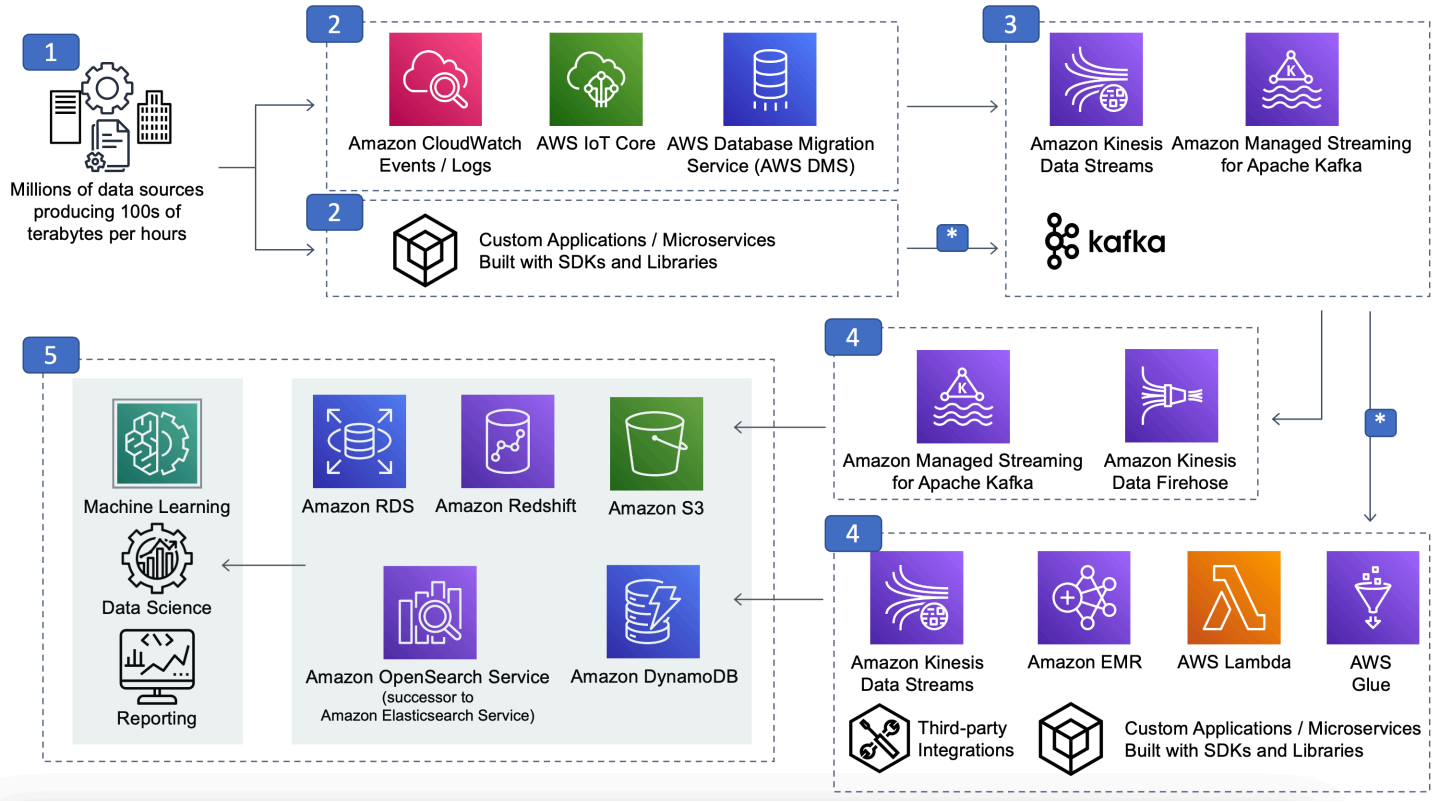


Figure 4: Streaming data analytics reference architecture

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

- Data sources
- Stream ingestion and producers
- Stream storage
- Stream processing and consumers
- 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.

We will review the five core components of streaming architecture first, and then discuss these specialized flows.

1. **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.
2. **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.
3. **Streaming storage**: Kinesis Data Streams, Amazon MSK, 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.
4. **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 Managed Service for Apache Flink for Apache Flink or Managed Service for Apache Flink 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, Amazon MSK, and Apache Kafka.

5. **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 that 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) that 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) that 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 whitepaper, 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 in the *Amazon Kinesis Data Streams Developer Guide*).
- **Streaming storage** — Kinesis Data Streams, Firehose, Amazon MSK, and Apache Kafka (Refer to Best Practices in Amazon Managed in *the Amazon Managed Streaming for Apache Kafka Developer Guide*).
- **Stream processing and consumers** — Managed Service for Apache Flink for Apache Flink, 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 Managed Service for Apache Flink for Apache Flink in the Amazon Managed Service for Apache Flink Developer Guide).

For more information, refer to the Build Modern Data Streaming Architectures on AWS whitepaper.

Remember separation of concerns. Separation of concerns is the application design principle that promotes segmenting an application into distinct, particular area of concerns. For example, 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 must write your own. Or perhaps both options are available. Many teams new to streaming incorrectly assume that everything must be written from scratch. Instead, consider services such as Kafka Connect Connectors for inbound and outbound traffic, AWS Lambda, and 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 storage. 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 de-aggregation 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.

- Amazon Kinesis Data Streams Developer Guide: Monitoring Amazon Kinesis Data Streams
- 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. For example, Kinesis Data Streams replicates to three different Availability Zones. With Apache Kafka and Amazon MSK, producers can be configured to require acknowledgement for partition leader as well as a configurable number of in-sync replica followers before considering the write successful. In these examples, 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 and 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: AWS Identity and Access Management
- AWS Lake Formation Developer Guide: Security in AWS Lake Formation

Operational analytics

Operational analytics refers to inter-disciplinary techniques and methodologies that aim to measure and improve day-to-day business performance in terms of increasing the efficiency of internal business processes and improving customer experience and value.

Traditional analytics like Business Intelligence (BI) provide each Line of Business (LOB) with insights to identify trends and take decisions based on what happened in the past.

But this is no longer sufficient. To deliver a good customer experience, organizations must continually measure their workload performance and quickly respond to operational inefficiencies for a better customer experience.

By using 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.

On the other hand, IT infrastructures are becoming increasingly distributed adding more complexity to the workloads in terms of identifying the operational data that captures the system's state, characterize its behavior, and finally rectify potential issues in the pipelines.

Several tools and methodologies have emerged that help companies keep their systems reliable. Every system or application must be instrumented to expose telemetry data that provides operational insights in real or near real time.

The telemetry data can be of different form of signals: logs, traces, and metrics. Traditionally this data came in the form of logs that represent a record of an event happened within an application,

server or a system operation. It can be of different types such as: application logs, security logs, system logs, audit trails, and infrastructure logs. Logs are usually used in troubleshooting and generating root-cause analysis for a system or application failure at a specific point in time.

Trace signal 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. It indicates a causal relationship between all the services being part of a distributed transaction. Organizations used to develop their own trace mechanisms but it is recommended to use existing tools that support a standard trace-context propagation format. The trace-context holds the information that links the producer of a message to its downstream consumers.

Metric data provides a point-in-time measure of the health of the system, such as resource consumptions in terms of CPU utilization. Metric signals offer an overview of the overall system health while reducing the manual effort to build these metrics and store them. With metrics, system operators can be notified in real time about anomalies in production environments and establish automated recovery process in case of a recurrent incident.

The signals mentioned above have different ways to be instrumented and provide different approaches to implement operational analytics use cases. Therefore, organizations must have an operational objective in mind from which they can work backwards to identify what data output they need from their system, which tool is better fit for their business and IT environment and finally what insights are needed to better understand their customers and improve their production resiliency.

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.

Connectivity: Operational data can emanate from a variety of data sources in different format with disparate volumes. For this reason, the operational system has to provide the capability to seamlessly integrate all the data with the least overhead for production application.

Scalability: The ability of the system to scale up and out to adapt to changes in the operational analytics workload in terms of storage or compute requirements.

Monitoring: You should be able to continuously monitor the operational system performance and get notified about the resource utilization and the overall health of your system.

Security: The access to the operational system must be secure. With Amazon OpenSearch Service, you can configure the domain to be accessible with an endpoint within your VPC or a public endpoint accessible to the internet. In addition to network-based access control, you must set up user authentication and authorization to secure the access to data based on business requirements. OpenSearch Service supports encryption at rest and in Transit.

Data durability: With operational analytics, the use cases differ as to the retention requirements. You should understand your business requirements in terms of analyzing historical data. With Amazon OpenSearch Service, you can retain more data with less cost using the UltraWarm and cold storage tiers.

Automation: The data lifecycle in your operational system should be automated in order to easily onboard new data pipelines and reduce the overhead of managing the lifecycle of the data. With Index State Management (ISM) in Amazon OpenSearch Service, you can create your own policies to automate the lifecycle management of indices stored in the service.

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

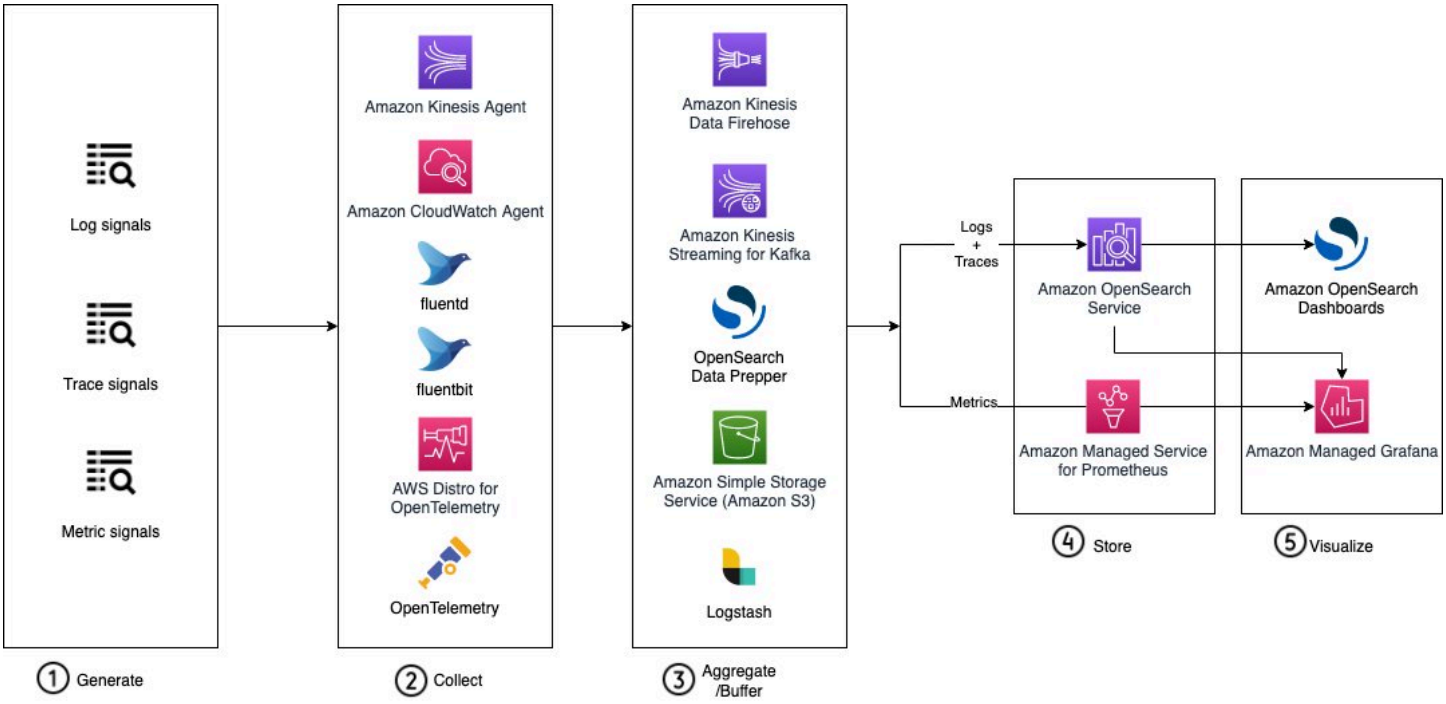


Figure 5: Operational analytics reference architecture

The reference architecture covers the data flow in an operational analytics use case. The Ingestion pipeline contains up to five stages as follows:

1. With your operational and business goal in mind, you should instrument your system/plate-form to **produce** the relevant type of signals such as various logs, traces, and metrics, and expose the data to a set of collectors. At this stage, you choose open-source instrumentation tools such as Jaeger or Zipkin. And if you plan to generate different type of signals, we recommend that you include signal correlation beginning with the design step. Open-source tools such as OpenTelemetry facilitate the context propagation by adding a Trace ID to all logs related to a specific request. This reduces the mean time to problem resolution by enhancing the observability of the system from multiple viewpoints.
2. The second step is to **collect** the telemetry data from the producers and deliver it to the aggregators or buffers. You can use native AWS services (such as Amazon Kinesis Agent, CloudWatch agents, or AWS Distro for OpenTelemetry) to let you instrument your applications just once, collect and correlate metrics and traces, along with contextual information and metadata about where the application is running. You can also use a number of lightweight shippers such as Fluentd to collect logs, Fluentbit to collect both logs and metrics, and open-source OpenTelemetry.

3. Before sending the data to Amazon OpenSearch Service, it is recommended that you **buffer or aggregate** information from the collectors to reduce the overall connections to the domain and use the batch (_bulk) API to send batches of documents rather than sending single documents. It is also possible at this stage (or at the collection stage) to transform and aggregate the data for the downstream analytics tools. To do this, you can use AWS services such as Amazon Data Firehose and Amazon Managed Streaming for Apache Kafka. For large-scale environments, you can use Amazon S3 to have a backup the data. It is also possible to use open-source tools such as OpenSearch Data Prepper for trace and log analytics, or you can use the open source version of Logstash (check compatibility with Amazon OpenSearch Service here).
4. Amazon OpenSearch Service makes it easy for you to index and **store** telemetry data to perform interactive analytics. Amazon OpenSearch Service is built to handle a large volume of structured and unstructured data from multiple data sources at high ingestion rates. Amazon OpenSearch Service integrates not only with AWS services but also with open-source tools as the ones listed previously. It is also possible to use Amazon Managed Service for Prometheus to **store** and **query** operational metrics. The service is integrated with Amazon Elastic Kubernetes Service (Amazon EKS), Amazon Elastic Container Service (Amazon ECS), and AWS Distro for Open Telemetry.
5. Amazon OpenSearch Service dashboard is the default **visualization** tool for data in Amazon OpenSearch Service. It also serves as a user interface for many of the OpenSearch plugins, including Observability, Security, Alerting, Index State Management, and SQL. You can also conduct interactive analysis and visualization on data with Piped Processing Language (PPL), a query interface. You can use Amazon Managed Grafana to complement Amazon OpenSearch Service on the visualization layer. And you connect Amazon Grafana to Amazon Managed Service for Prometheus to query, **visualize**, alert on, and understand metric data.

Configuration notes

As shared in the previous section, there are different options and a non-exhaustive list of tools that you can choose from to implement an operational analytics pipeline. A list of configuration parameters to take into consideration for a well-architected operational pipeline is provided.

Define operational goals and business requirements: As a best practice, you should always start by identifying your operational goals, and what business outcome you must reach. Think about who are your end users, what are the insights to help drive their decisions, and how they will access these insights. After you define the business requirements, you can start designing your technical

pipeline, establishing the integration options in your environment, and reviewing the skill sets you have, to choose the right option.

Choose a 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.

Ingestion pipeline: You should make sure that your ingestion framework is reusable and extensible to be able to scale and include new use cases on the long term, otherwise, check which parts of your infrastructure would require modernization.

Production ready tools and services: AWS offers a set of managed services that are production ready and which eliminate the operational overhead of managing the infrastructure, such as Amazon OpenSearch Service. As shared in the reference architecture, you can also integrate open source tools, such as OpenSearch Data Prepper, to transform and aggregate the operational data for downstream analytics and visualizations.

Sizing OpenSearch domain: The first step in sizing an OpenSearch cluster is to check your data size, and identify your storage and query requirements. Estimate the number of active shards you will have per index based on your input data, and the shard size that you identify. Then, estimate your vCPU requirements and choose the type of instances that will be able to handle both storage and vCPUs. Plan for time to benchmark the domain with a realistic dataset using OpenSearch Benchmark, tune the configuration and iterate until you meet the performances required in terms of Throughout, Search Latency, and Index Latency. For more information, see Sizing Amazon OpenSearch Service domains and Best practices for configuring your Amazon OpenSearch Service domain.

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 can also help address storage cost.

Performance: There are multiple parameters to consider when thinking about performance and it is always specific to each workload. However, Amazon OpenSearch Service offers features that you can already enable in your domain, such as Auto-Tune that automatically deploys optional changes to improve cluster speed and stability. Other items to take into consideration include using the `_bulk` API to load data into OpenSearch, and only indexing data fields that need be searchable.

Define security requirements: Make sure to set up your domain inside a virtual Private Cloud (VPC) to secure the traffic to your domain. Apply the least privilege access approach with restrictive

access policies, or with fine-grained access control for OpenSearch dashboards. OpenSearch Service also offers encryption of data at rest and in transit.

Monitor all involved components: Monitor all involved components with metrics in Amazon CloudWatch. With the CloudWatch metrics available for Amazon OpenSearch Service, you can monitor the overall cluster health, you can also check the performance of individuals nodes and monitor EBS volume metrics. It is also a best practice to set CloudWatch alarms to get notified about any issues that your production domain encounters. You can start by setting the following alarms:

- `CPUUtilization` maximum is >= 80% for 15 minutes, 3 consecutive times
- `ClusterStatus.yellow` maximum is >= 1 for 1 minute, 1 consecutive time
- `JVMMemoryPressure` maximum is >= 80% for 5 minutes, 3 consecutive times
- `FreeStorageSpace` minimum is <= 25% of the storage space for 1 minute, 1 consecutive time

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. This gives decision makers the opportunity to explore and interpret information in an interactive visual environment to 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 to 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, Amazon QuickSight SPICE, and web applications automatically scale up server capacity to accommodate a large number of concurrent users without any manual intervention in terms of provisioning additional capacity for data, load balancing, and other services.

Connectivity: BI applications must be able to not only connect with data platforms such as traditional data warehouses and databases, but also support connectivity to a data lake and modern data 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 data sources, data sets, 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.

Perform advanced analytics

Modern BI applications must be able to discover hidden insights from your data, perform forecasting and what-if analysis, or add easy-to-understand natural language narratives to dashboards. The business users need the ability to perform analytics without deep statistical and machine learning knowledge.

Amazon QuickSight ML Insights provide features that make it easy to discover hidden trends and outliers, identify key business drivers, and perform powerful what-if analysis and forecasting with no technical or ML experience.

Enable self-service business intelligence

The common challenges of BI tools are how to make data more accessible to more people without extensive user training and technical understanding. Data must be available in all format - raw, semi-processed and processed. Self-service BI should allow users to interact with data on an as-needed-basis without involving IT.

Amazon QuickSight Q allows user to ask business questions in natural language and receive answers with relevant visualizations that help them gain insights from the data. QuickSight Q uses machine learning to interpret the intent of a question and analyze the correct data to provide accurate answers to business questions quickly

Reference architecture

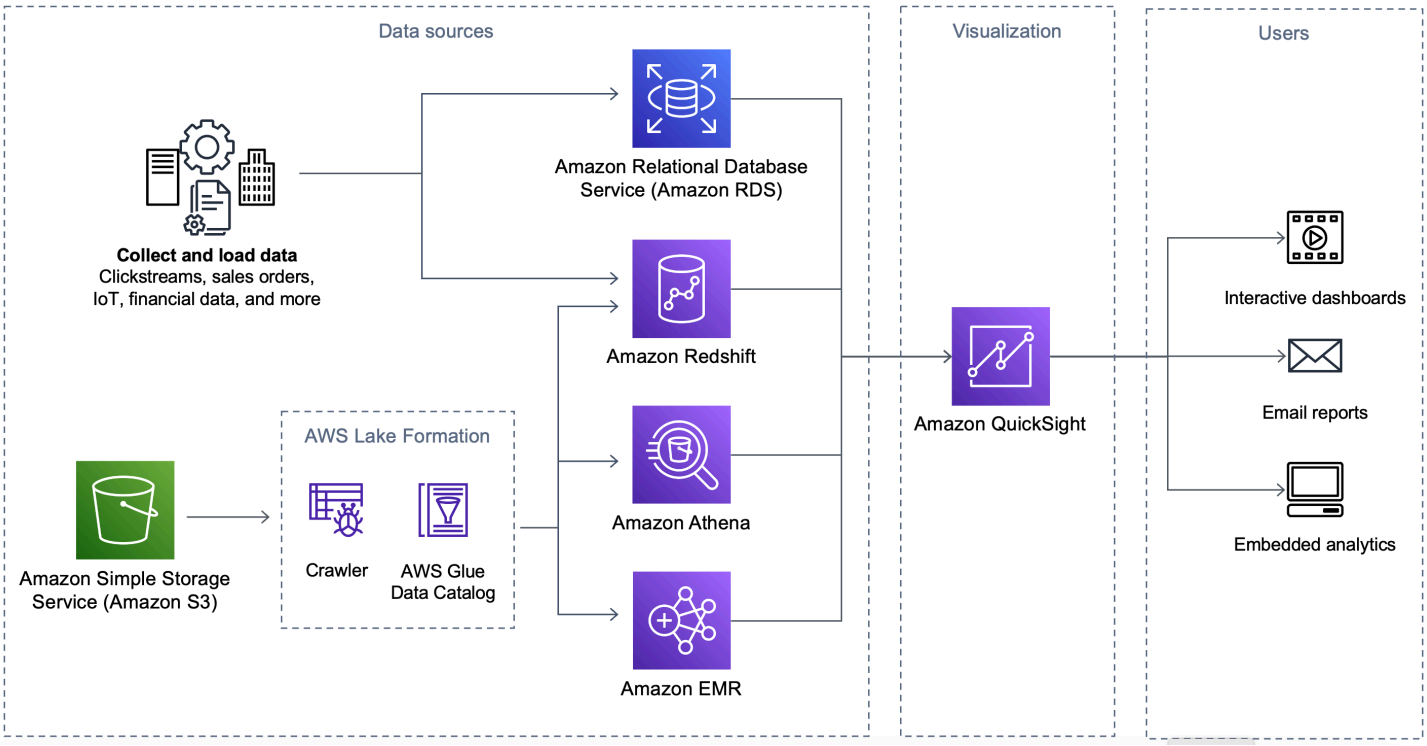


Figure 6: QuickSight dashboard end-to-end design

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, and ServiceNow. 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, and secure firewalls.

Visualization Tool: Amazon QuickSight.

Consumers: Visual dashboard consumers accessing a 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 VPCs and restrict security groups to only the 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. To ease flow and remove confusion, set up QuickSight and single sign-on (SSO) such that email addresses for end users are automatically synced at their first login. 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 Amazon Athena (common services used in data warehouse, data lake or modern data 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) that 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 500M 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 AWS Glue DataBrew, or techniques, such as materialized views, can be employed to achieve this. After uploading the dataset, users

can add calculated fields to a dataset during the data preparation or from the analysis page for additional insights provided data.

Data mesh

A *data mesh* is an architectural framework that enables domain teams to perform cross-domain data analysis through distributed, decentralized ownership.

Organizations have multiple data sources from different lines of business that must be integrated for analytics. Managing all these data sources from a central data repository can be challenging. Similar to how application architecture has involved into building microservices rather than a single application entity, data teams are exploring ways to modularize their data platforms to become federated, decentralized solutions.

A data mesh is an analytics design pattern that effectively unites the disparate data sources and links them together through self-service data sharing and governance guidelines. Business functions can maintain control over how shared data is accessed, who can access it and when it can be accessed. Organizations that have built data lakes, data warehouses and other data repositories, and require these environments to be more connected, could benefit from a data mesh architecture.

The trade off to implementing a data mesh is that a data mesh adds complexities to architecture but also brings efficiency by improving data searchability, accessibility, security and scalability.

A data mesh transfers data control to domain experts who create meaningful data products within a decentralized governance framework. Data consumers request access to the data products and seek approvals or changes directly from data owners. As a result, everyone gets faster access to relevant data, and faster access improves business agility.

A data mesh may be suitable for customers who:

- Have a well-established data strategy
- Have a current implementation of a modern data architecture
- Have decoupled business units that operate autonomously
- Need to share data across business units, or with external partners
- Require consistent data governance across multiple teams that aren’t part of a single organization

- Need to have quick delivery cycles with well-defined agile practices, and are willing to iterate changes from lessons learned

Technology, people, and processes are the key principles that help deliver and maintain a successful data mesh. The people and processes can be identified as follows:

- **Data owner:** A data mesh features data domains as nodes, which exist in data lake accounts; it is founded in decentralization and distribution of data responsibility to people closest to the data, which become data domain owners.
- **Data steward:** Federated data governance is how data products are shared. Delivering discoverable metadata auditability based on federated decision-making and accountability structures falls to the data steward.
- **Data engineer:** A data producer contributes one or more data products to a central catalog in a data mesh account. Data products must be autonomous, discoverable, secure, and reusable.
- **Data consumer:** The platform streamlines the experience of data users to discover, access, and use data products. It streamlines the experience of data consumers to easily consume and drive value from the data.

Characteristics

The following are characteristics of a data mesh:

- **Data diversity:** Treats data platforms as independent data domains, connecting data domains into the mesh to create business-oriented data products that can support strategic goals. The information persisted in their respective environments comes from different applications or source systems adding to the overall data diversity that analysts and data scientists benefit from.
- **Data democritization:** Rather than try to combine multiple domains into a centrally managed data lake, data is intentionally left distributed. By adopting this approach, your organization's data becomes democratized and becomes assessible to more teams.
- **Data governance:** Improve data governance by pushing data access policy down into the data domains. Large enterprise organizations experience challenges when scaling their data governance to the number of subscribers because this is managed centrally. A data mesh allows for disparate teams to inherit the data governance policy from the data producer domain.
- **Searchability:** Establishing a central mechanism for data discovery is valuable for analysts and researchers to know what data is available. An enterprise-level data catalog contains the

metadata of the organization's data assets. The data catalog contains data attributes, data quality, data classification, and a business glossary of the data.

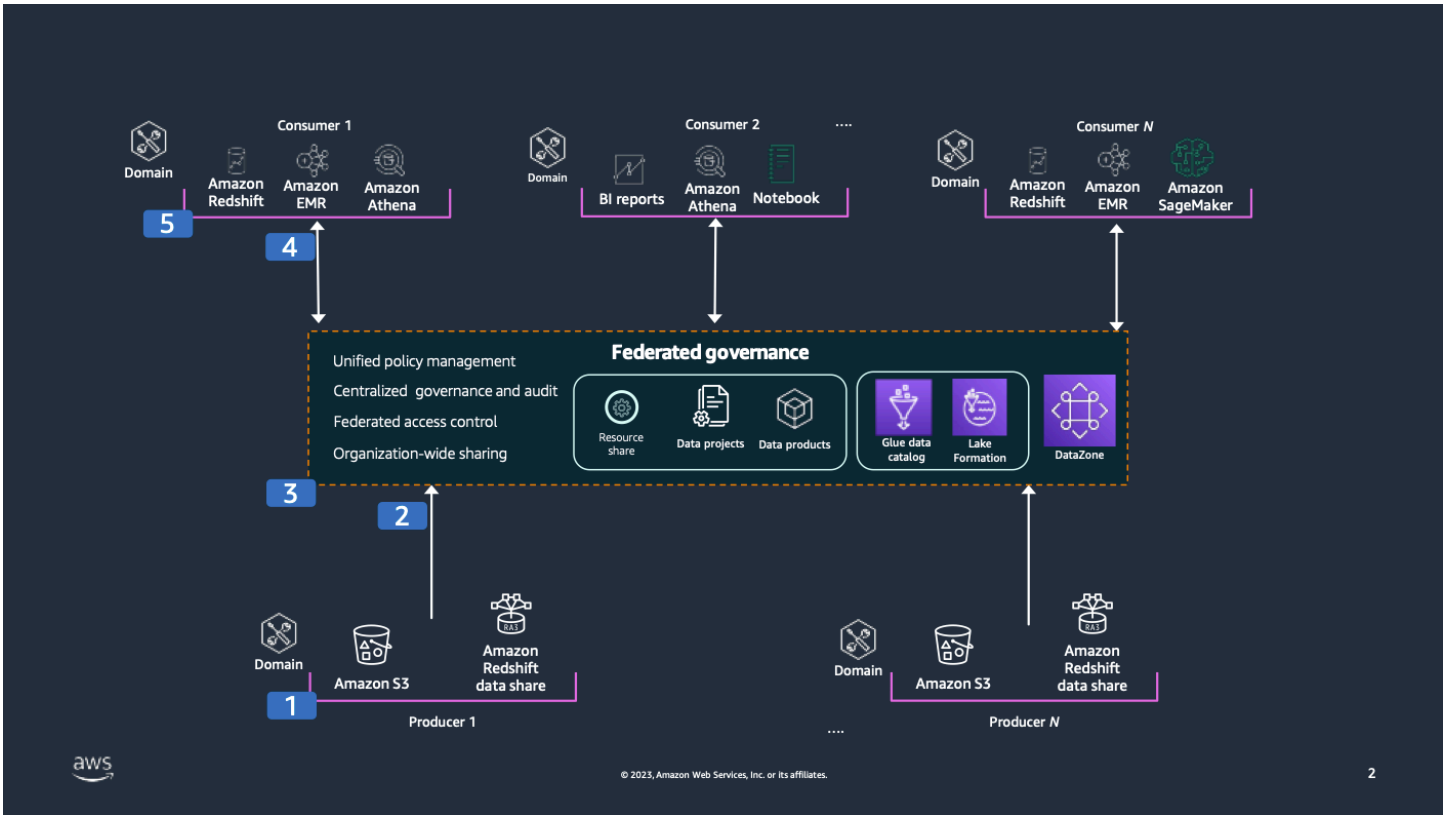
- **Data sharing:** Provide self-service data sharing features to allow domain owners to grant access to consumers.
- **Increased flexibility:** Increase data flexibility by implementing an enterprise data mesh. A data mesh provides organizations greater agility as data becomes widely available and supports faster data-driven business decisions.
- **Reusability:** A data mesh increases the adoption of reusable data pipeline design patterns to share data across your organization.

Design

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 the right personas have access to the right data. The technical implementation of data governance, such as collecting lineage, validating data quality, 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. This requires data domains to expose a set of interfaces that make data consumable while enforcing appropriate access controls and audit tracking.

Reference architecture



Data mesh reference architecture

Each consumer, producer, and central governance layer are their own separate data domain and typically reside in their own separate AWS account. Information is shared between domains.

1. Data producers are source systems that generate data, which is shared throughout the organization. Data producers can be an application, data stream, data lake, or data warehouse – essentially a domain that either generates or updates data. The business owners that are responsible for the data producers must have their data attributes classified for consumers to inherit the classification so data processing and data access to that data meets the organization's or industry's data governance policy.
2. Metadata relating to producer data must be shared with the central federated data catalog. Data owner information, data quality information, data location and any other metadata must be shared with the central data catalog at the earliest possible opportunity.
3. The federated governance layer is a centralized data governance domain that supports data cataloging, asset discoverability, permission management, and a central log for audit history.

4. Data governance rules such as data classifications, access permissions and metadata is shared with the consumer system. This is typically shared using an API connection but can also be shared as a manual extract.
5. Data consumers are systems that consume information typically for analytical or data science type workloads. Information is either copied from or accessed directly from the producer domains through the federated governance environment. Access permissions are then inherited and propagated into the respective system to ensure the right people have access to the right data.

For more details, see Design a data mesh architecture using AWS Lake Formation and AWS Glue and What is a Data Mesh?

Conclusion

This lens provided 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 whitepaper also discussed the AWS Well-Architected Framework 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 time 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 whitepaper to help you ensure that your analytics applications are well architected.

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Document revisions

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Change	Description	Date
Major update	Updated content throughout pillars. Added new scenario and updated reference architectures.	December 22, 2023
Minor update	Fixed broken links.	April 6, 2023
Minor update	Contributors updated.	January 5, 2023
Major update	Added Sustainability content and numerous updates throughout.	November 17, 2022
Minor update	Updates throughout and added placeholder for Sustainability.	September 14, 2022
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AWS Glossary

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