AWS-Certified-Data-Engineer-Associate Dumps

AWS Certified Data Engineer - Associate (DEA-C01)

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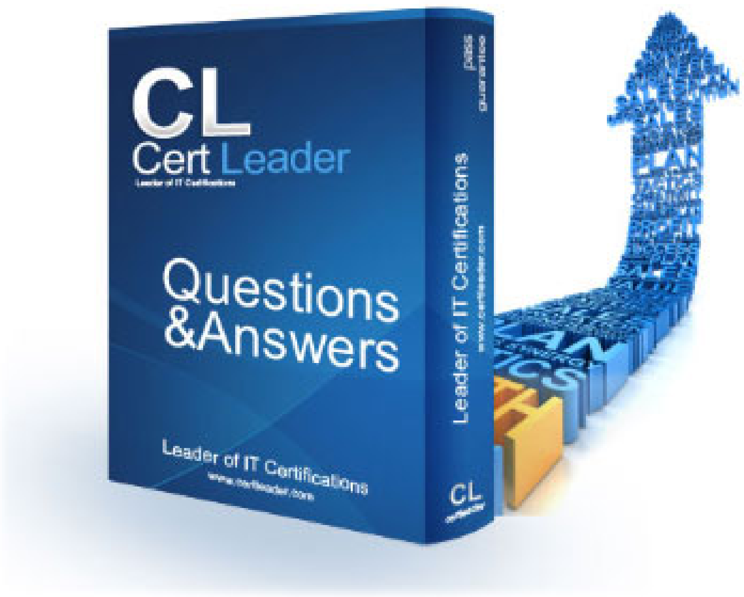

NEW QUESTION 1
A data engineer needs to join data from multiple sources to perform a one-time analysis job. The data is stored in Amazon DynamoDB, Amazon RDS, Amazon Redshift, and Amazon S3.
Which solution will meet this requirement MOST cost-effectively?

A. Use an Amazon EMR provisioned cluster to read from all source
B. Use Apache Spark to join the data and perform the analysis.
C. Copy the data from DynamoDB, Amazon RDS, and Amazon Redshift into Amazon S3. Run Amazon Athena queries directly on the S3 files.
D. Use Amazon Athena Federated Query to join the data from all data sources.
E. Use Redshift Spectrum to query data from DynamoDB, Amazon RDS, and Amazon S3 directly from Redshift.

Answer: C

Explanation:
Amazon Athena Federated Query is a feature that allows you to query data from multiple sources using standard SQL. You can use Athena Federated Query to join data from Amazon DynamoDB, Amazon RDS, Amazon Redshift, and Amazon S3, as well as other data sources such as MongoDB, Apache HBase, and Apache Kafka1. Athena Federated Query is a serverless and interactive service, meaning you do not need to provision or manage any infrastructure, and you only pay for the amount of data scanned by your queries. Athena Federated Query is the most cost-effective solution for performing a one-time analysis job on data from multiple sources, as it eliminates the need to copy or move data, and allows you to query data directly from the source.
The other options are not as cost-effective as Athena Federated Query, as they involve additional steps or costs. Option A requires you to provision and pay for an Amazon EMR cluster, which can be expensive and time-consuming for a one-time job. Option B requires you to copy or move data from DynamoDB, RDS, and Redshift to S3, which can incur additional costs for data transfer and storage, and also introduce latency and complexity. Option D requires you to have an existing Redshift cluster, which can be costly and may not be necessary for a one-time job. Option D also does not supportquerying data from RDS directly, so you would need to use Redshift Federated Query to access RDS data, which adds another layer of complexity2. References:
? Amazon Athena Federated Query
? Redshift Spectrum vs Federated Query

NEW QUESTION 2
A company stores datasets in JSON format and .csv format in an Amazon S3 bucket. The company has Amazon RDS for Microsoft SQL Server databases, Amazon DynamoDB tables that are in provisionedcapacity mode, and an Amazon Redshift cluster. A data engineering team must develop a solution that will give data scientists the ability to query all data sources by using syntax similar to SQL.
Which solution will meet these requirements with the LEAST operational overhead?

A. Use AWS Glue to crawl the data source
B. Store metadata in the AWS Glue Data Catalo
C. Use Amazon Athena to query the dat
D. Use SQL for structured data source
E. Use PartiQL for data that is stored in JSON format.
F. Use AWS Glue to crawl the data source
G. Store metadata in the AWS Glue Data Catalo
H. Use Redshift Spectrum to query the dat
I. Use SQL for structured data source
J. Use PartiQL for data that is stored in JSON format.
K. Use AWS Glue to crawl the data source
L. Store metadata in the AWS Glue Data Catalo
M. Use AWS Glue jobs to transform data that is in JSON format to Apache Parquet or .csv forma
N. Store the transformed data in an S3 bucke
O. Use Amazon Athena to query the original and transformed data from the S3 bucket.
P. Use AWS Lake Formation to create a data lak
Q. Use Lake Formation jobs to transform the data from all data sources to Apache Parquet forma
R. Store the transformed data in an S3 bucke
S. Use Amazon Athena or Redshift Spectrum to query the data.

Answer: A

Explanation:
The best solution to meet the requirements of giving data scientists the ability to query all data sources by using syntax similar to SQL with the least operational overhead is to use AWS Glue to crawl the data sources, store metadata in the AWS Glue Data Catalog, use Amazon Athena to query the data, use SQL for structured data sources, and use PartiQL for data that is stored in JSON format.
AWS Glue is a serverless data integration service that makes it easy to prepare, clean, enrich, and move data between data stores1. AWS Glue crawlers are processes that connect to a data store, progress through a prioritized list of classifiers to determine the schema for your data, and then create metadata tables in the Data Catalog2. The Data Catalog is a persistent metadata store that contains table definitions, job definitions, and other control information to help you manage your AWS Glue components3. You can use AWS Glue to crawl the data sources, such as Amazon S3, Amazon RDS for Microsoft SQL Server, and Amazon DynamoDB, and store the metadata in the Data Catalog.
Amazon Athena is a serverless, interactive query service that makes it easy to analyze data directly in Amazon S3 using standard SQL or Python4. Amazon Athena also supports PartiQL, a SQL-compatible query language that lets you query, insert, update, and delete data from semi-structured and nested data, such as JSON. You can use Amazon Athena to query the data from the Data Catalog using SQL for structured data sources, such as .csv files and relational databases, and PartiQL for data that is stored in JSON format. You can also use Athena to query data from other data sources, such as Amazon Redshift, using federated queries.
Using AWS Glue and Amazon Athena to query all data sources by using syntax similar to SQL is the least operational overhead solution, as you do not need to provision, manage, or scale any infrastructure, and you pay only for the resources you use. AWS Glue charges you based on the compute time and the data processed by your crawlers and ETL jobs1. Amazon Athena charges you based on the amount of data scanned by your queries. You can also reduce the cost and improve the performance of your queries by using compression, partitioning, and columnar formats for your data in Amazon S3.
Option B is not the best solution, as using AWS Glue to crawl the data sources, store metadata in the AWS Glue Data Catalog, and use Redshift Spectrum to query the data, would incur more costs and complexity than using Amazon Athena. Redshift Spectrum is a feature of Amazon Redshift, a fully managed data warehouse service, that allows you to query and join data across your data warehouse and your data lake using standard SQL. While Redshift Spectrum is powerful and useful for many data warehousing scenarios, it is not necessary or cost-effective for querying all data sources by using syntax similar to SQL. Redshift Spectrum charges you based on the amount of data scanned by your queries, which is similar to Amazon Athena, but it also requires you to have an Amazon Redshift cluster, which charges you based on the node type, the number of nodes, and the duration of the cluster5. These costs can add up quickly, especially if you have large volumes of data and complex queries. Moreover, using Redshift Spectrum would introduce additional latency and complexity, as you

would have to provision and manage the cluster, and create an external schema and database for the data in the Data Catalog, instead of querying it directly from Amazon Athena.
Option C is not the best solution, as using AWS Glue to crawl the data sources, store metadata in the AWS Glue Data Catalog, use AWS Glue jobs to transform data that is in JSON format to Apache Parquet or .csv format, store the transformed data in an S3 bucket, and use Amazon Athena to query the original and transformed data from the S3 bucket, would incur more costs and complexity than using Amazon Athena with PartiQL. AWS Glue jobs are ETL scripts that you can write in Python or Scala to transform your data and load it to your target data store. Apache Parquet is a columnar storage format that can improve the performance of analytical queries by reducing the amount of data that needs to be scanned and providing efficient compression and encoding schemes6. While using AWS Glue jobs and Parquet can improve the performance and reduce the cost of your queries, they would also increase the complexity and the operational overhead of the data pipeline, as you would have to write, run, and monitor the ETL jobs, and store the transformed data in a separate location in Amazon S3. Moreover, using AWS Glue jobs and Parquet would introduce additional latency, as you would have to wait for the ETL jobs to finish before querying the transformed data.
Option D is not the best solution, as using AWS Lake Formation to create a data lake, use Lake Formation jobs to transform the data from all data sources to Apache Parquet format, store the transformed data in an S3 bucket, and use Amazon Athena or RedshiftSpectrum to query the data, would incur more costs and complexity than using Amazon Athena with PartiQL. AWS Lake Formation is a service that helps you centrally govern, secure, and globally share data for analytics and machine learning7. Lake Formation jobs are ETL jobs that you can create and run using the Lake Formation console or API. While using Lake Formation and Parquet can improve the performance and reduce the cost of your queries, they would also increase the complexity and the operational overhead of the data pipeline, as you would have to create, run, and monitor the Lake Formation jobs, and store the transformed data in a separate location in Amazon S3. Moreover, using Lake Formation and Parquet would introduce additional latency, as you would have to wait for the Lake Formation jobs to finish before querying the transformed data. Furthermore, using Redshift Spectrum to query the data would also incur the same costs and complexity as mentioned in option B. References:
? What is Amazon Athena?
? Data Catalog and crawlers in AWS Glue
? AWS Glue Data Catalog
? Columnar Storage Formats
? AWS Certified Data Engineer - Associate DEA-C01 Complete Study Guide
? AWS Glue Schema Registry
? What is AWS Glue?
? Amazon Redshift Serverless
? Amazon Redshift provisioned clusters
? [Querying external data using Amazon Redshift Spectrum]
? [Using stored procedures in Amazon Redshift]
? [What is AWS Lambda?]
? [PartiQL for Amazon Athena]
? [Federated queries in Amazon Athena]
? [Amazon Athena pricing]
? [Top 10 performance tuning tips for Amazon Athena]
? [AWS Glue ETL jobs]
? [AWS Lake Formation jobs]

NEW QUESTION 3
A company uses AWS Step Functions to orchestrate a data pipeline. The pipeline consists of Amazon EMR jobs that ingest data from data sources and store the data in an Amazon S3 bucket. The pipeline also includes EMR jobs that load the data to Amazon Redshift.
The company's cloud infrastructure team manually built a Step Functions state machine. The cloud infrastructure team launched an EMR cluster into a VPC to support the EMR jobs. However, the deployed Step Functions state machine is not able to run the EMR jobs.
Which combination of steps should the company take to identify the reason the Step Functions state machine is not able to run the EMR jobs? (Choose two.)

A. Use AWS CloudFormation to automate the Step Functions state machine deploymen
B. Create a step to pause the state machine during the EMR jobs that fai
C. Configure the step to wait for a human user to send approval through an email messag
D. Include details of the EMR task in the email message for further analysis.
E. Verify that the Step Functions state machine code has all IAM permissions that are necessary to create and run the EMR job
F. Verify that the Step Functions state machine code also includes IAM permissions to access the Amazon S3 buckets that the EMR jobs us
G. Use Access Analyzer for S3 to check the S3 access properties.
H. Check for entries in Amazon CloudWatch for the newly created EMR cluste
I. Change the AWS Step Functions state machine code to use Amazon EMR on EK
J. Change the IAM access policies and the security group configuration for the Step Functions state machine code to reflect inclusion of Amazon Elastic Kubernetes Service (Amazon EKS).
K. Query the flow logs for the VP
L. Determine whether the traffic that originates from the EMR cluster can successfully reach the data provider
M. Determine whether any security group that might be attached to the Amazon EMR cluster allows connections to the data source servers on the informed ports.
N. Check the retry scenarios that the company configured for the EMR job
O. Increase the number of seconds in the interval between each EMR tas
P. Validate that each fallback state has the appropriate catch for each decision stat
Q. Configure an Amazon Simple Notification Service (Amazon SNS) topic to store the error messages.

Answer: BD

Explanation:
To identify the reason why the Step Functions state machine is not able to run the EMR jobs, the company should take the following steps:
? Verify that the Step Functions state machine code has all IAM permissions that are necessary to create and run the EMR jobs. The state machine code should have an IAM role that allows it to invoke the EMR APIs, such as RunJobFlow, AddJobFlowSteps, and DescribeStep. The state machine code should also have IAM permissions to access the Amazon S3 buckets that the EMR jobs use as input and output locations. The company can use Access Analyzer for S3 to check the access policies and permissions of the S3 buckets12. Therefore, option B is correct.
? Query the flow logs for the VPC. The flow logs can provide information about the network traffic to and from the EMR cluster that is launched in the VPC. The company can use the flow logs to determine whether the traffic that originates from the EMR cluster can successfully reach the data providers, such as Amazon RDS, Amazon Redshift, or other external sources. The company can also determine whether any security group that might be attached to the EMR cluster allows connections to the data source servers on the informed ports. The company can use Amazon VPC Flow Logs or Amazon CloudWatch Logs Insights to query the flow logs3 . Therefore, option D is correct.
Option A is incorrect because it suggests using AWS CloudFormation to automate the Step Functions state machine deployment. While this is a good practice to ensure consistency and repeatability of the deployment, it does not help to identify the reasonwhy the state machine is not able to run the EMR jobs. Moreover, creating a step to pause the state machine during the EMR jobs that fail and wait for a human user to send approval through an email message is not a reliable way to troubleshoot the issue. The company should use the Step Functions console or API to monitor the execution history and status of the state machine, and use Amazon CloudWatch to view the logs and metrics of the EMR jobs . Option C is incorrect because it suggests changing the AWS Step Functions state

machine code to use Amazon EMR on EKS. Amazon EMR on EKS is a service that allows you to run EMR jobs on Amazon Elastic Kubernetes Service (Amazon EKS) clusters. While this service has some benefits, such as lower cost and faster execution time, it does not support all the features and integrations that EMR on EC2 does, such as EMR Notebooks, EMR Studio, and EMRFS. Therefore, changing the state machine code to use EMR on EKS may not be compatible with the existing data pipeline and may introduce new issues. Option E is incorrect because it suggests checking the retry scenarios that the company configured for the EMR jobs. While this is a good practice to handle transient failures and errors, it does not help to identify the root cause of why the state machine is not able to run the EMR jobs. Moreover, increasing the number of seconds in the interval between each EMR task may not improve the success rate of the jobs, and may increase the execution time and cost of the state machine. Configuring an Amazon SNS topic to store the error messages may help to notify the company of any failures, but it does not provide enough information to troubleshoot the issue.
References:
? 1: Manage an Amazon EMR Job - AWS Step Functions
? 2: Access Analyzer for S3 - Amazon Simple Storage Service
? 3: Working with Amazon EMR and VPC Flow Logs - Amazon EMR
? [4]: Analyzing VPC Flow Logs with Amazon CloudWatch Logs Insights - Amazon Virtual Private Cloud
? [5]: Monitor AWS Step Functions - AWS Step Functions
? [6]: Monitor Amazon EMR clusters - Amazon EMR
? [7]: Amazon EMR on Amazon EKS - Amazon EMR

NEW QUESTION 4
A data engineer needs to use an Amazon QuickSight dashboard that is based on Amazon Athena queries on data that is stored in an Amazon S3 bucket. When the data engineer connects to the QuickSight dashboard, the data engineer receives an error message that indicates insufficient permissions.
Which factors could cause to the permissions-related errors? (Choose two.)

A. There is no connection between QuickSgqht and Athena.
B. The Athena tables are not cataloged.
C. QuickSiqht does not have access to the S3 bucket.
D. QuickSight does not have access to decrypt S3 data.
E. There is no 1AM role assigned to QuickSiqht.

Answer: CD

Explanation:
QuickSight does not have access to the S3 bucket and QuickSight does not have access to decrypt S3 data are two possible factors that could cause the permissions- related errors. Amazon QuickSight is a business intelligence service that allows you to create and share interactive dashboards based on various data sources, including Amazon Athena. Amazon Athena is a serverless query service that allows you to analyze data stored in Amazon S3 using standard SQL. To use an Amazon QuickSight dashboard that is based on Amazon Athena queries on data that is stored in an Amazon S3 bucket, you need to grant QuickSight access to both Athena and S3, as well as any encryption keys that are used to encrypt the S3 data. If QuickSight does not have access to the S3 bucket or the encryption keys, it will not be able to read the data from Athena and display it on the dashboard, resulting in an error message that indicates insufficient permissions.
The other options are not factors that could cause the permissions-related errors. Option A, there is no connection between QuickSight and Athena, is not a factor, as QuickSight supports Athena as a native data source, and you can easily create a connection between them using the QuickSight console or the API. Option B, the Athena tables are not cataloged, is not a factor, as QuickSight can automatically discover the Athena tables that are cataloged in the AWS Glue Data Catalog, and you can also manually specify the Athena tables that are not cataloged. Option E, there is no IAM role assigned to QuickSight, is not a factor, as QuickSight requires an IAM role to access any AWS data sources, including Athena and S3, and you can create and assign an IAM role to QuickSight using the QuickSight console or the API. References:
? Using Amazon Athena as a Data Source
? Granting Amazon QuickSight Access to AWS Resources
? Encrypting Data at Rest in Amazon S3

NEW QUESTION 5
A manufacturing company wants to collect data from sensors. A data engineer needs to implement a solution that ingests sensor data in near real time.
The solution must store the data to a persistent data store. The solution must store the data in nested JSON format. The company must have the ability to query from the data store with a latency of less than 10 milliseconds.
Which solution will meet these requirements with the LEAST operational overhead?

A. Use a self-hosted Apache Kafka cluster to capture the sensor dat
B. Store the data in Amazon S3 for querying.
C. Use AWS Lambda to process the sensor dat
D. Store the data in Amazon S3 for querying.
E. Use Amazon Kinesis Data Streams to capture the sensor dat
F. Store the data in Amazon DynamoDB for querying.
G. Use Amazon Simple Queue Service(Amazon SQS) to buffer incomingsensor dat
H. Use AWS Glue to store thedata in Amazon RDS for querying.

Answer: C

Explanation:
Amazon Kinesis Data Streams is a service that enables you to collect, process, and analyze streaming data in real time. You can use Kinesis Data Streams to capture sensor data from various sources, such as IoT devices, web applications, or mobile apps. You can create data streams that can scale up to handle any amount of data from thousands of producers. You can also use the Kinesis Client Library (KCL) or the Kinesis Data Streams API to write applications that process and analyze the data in the streams1. Amazon DynamoDB is a fully managed NoSQL database service that provides fast and predictable performance with seamless scalability. You can use DynamoDB to store the sensor data in nested JSON format, as DynamoDB supports document data types, such as lists and maps. You can also use DynamoDB to query the data with a latency of less than 10 milliseconds, as DynamoDB offers single-digit millisecond performance for any scale of data. You can use the DynamoDB API or the AWS SDKs to perform queries on the data, such as using key-value lookups, scans, or queries2.
The solution that meets the requirements with the least operational overhead is to use Amazon Kinesis Data Streams to capture the sensor data and store the data in Amazon DynamoDB for querying. This solution has the following advantages:
? It does not require you to provision, manage, or scale any servers, clusters, or queues, as Kinesis Data Streams and DynamoDB are fully managed services that handle all the infrastructure for you. This reduces the operational complexity and cost of running your solution.
? It allows you to ingest sensor data in near real time, as Kinesis Data Streams can capture data records as they are produced and deliver them to your applications within seconds. You can also use Kinesis Data Firehose to load the data from the streams to DynamoDB automatically and continuously3.
? It allows you to store the data in nested JSON format, as DynamoDB supports document data types, such as lists and maps. You can also use DynamoDB Streams to capturechanges in the data and trigger actions, such as sending notifications or updating other databases.

? It allows you to query the data with a latency of less than 10 milliseconds, as DynamoDB offers single-digit millisecond performance for any scale of data. You can also use DynamoDB Accelerator (DAX) to improve the read performance by caching frequently accessed data.
Option A is incorrect because it suggests using a self-hosted Apache Kafka cluster to capture the sensor data and store the data in Amazon S3 for querying. This solution has the following disadvantages:
? It requires you to provision, manage, and scale your own Kafka cluster, either on EC2 instances or on-premises servers. This increases the operational complexity and cost of running your solution.
? It does not allow you to query the data with a latency of less than 10 milliseconds, as Amazon S3 is an object storage service that is not optimized for low-latency queries. You need to use another service, such as Amazon Athena or Amazon Redshift Spectrum, to query the data in S3, which may incur additional costs and latency.
Option B is incorrect because it suggests using AWS Lambda to process the sensor data and store the data in Amazon S3 for querying. This solution has the following disadvantages:
? It does not allow you to ingest sensor data in near real time, as Lambda is a serverless compute service that runs code in response to events. You need to use another service, such as API Gateway or Kinesis Data Streams, to trigger Lambda functions with sensor data, which may add extra latency and complexity to your solution.
? It does not allow you to query the data with a latency of less than 10 milliseconds, as Amazon S3 is an object storage service that is not optimized for low-latency queries. You need to use another service, such as Amazon Athena or Amazon Redshift Spectrum, to query the data in S3, which may incur additional costs and latency.
Option D is incorrect because it suggests using Amazon Simple Queue Service (Amazon SQS) to buffer incoming sensor data and use AWS Glue to store the data in Amazon RDS for querying. This solution has the following disadvantages:
? It does not allow you to ingest sensor data in near real time, as Amazon SQS is a message queue service that delivers messages in a best-effort manner. You need to use another service, such as Lambda or EC2, to poll the messages from the queue and process them, which may add extra latency and complexity to your solution.
? It does not allow you to store the data in nested JSON format, as Amazon RDS is a relational database service that supports structured data types, such as tables and columns. You need to use another service, such as AWS Glue, to transform the data from JSON to relational format, which may add extra cost and overhead to your solution.
References:
? 1: Amazon Kinesis Data Streams - Features
? 2: Amazon DynamoDB - Features
? 3: Loading Streaming Data into Amazon DynamoDB - Amazon Kinesis Data Firehose
? [4]: Capturing Table Activity with DynamoDB Streams - Amazon DynamoDB
? [5]: Amazon DynamoDB Accelerator (DAX) - Features
? [6]: Amazon S3 - Features
? [7]: AWS Lambda - Features
? [8]: Amazon Simple Queue Service - Features
? [9]: Amazon Relational Database Service - Features
? [10]: Working with JSON in Amazon RDS - Amazon Relational Database Service
? [11]: AWS Glue - Features

NEW QUESTION 6
A data engineer must orchestrate a data pipeline that consists of one AWS Lambda function and one AWS Glue job. The solution must integrate with AWS services.
Which solution will meet these requirements with the LEAST management overhead?

A. Use an AWS Step Functions workflow that includes a state machin
B. Configure the state machine to run the Lambda function and then the AWS Glue job.
C. Use an Apache Airflow workflow that is deployed on an Amazon EC2 instanc
D. Define a directed acyclic graph (DAG) in which the first task is to call the Lambda function and the second task is to call the AWS Glue job.
E. Use an AWS Glue workflow to run the Lambda function and then the AWS Glue job.
F. Use an Apache Airflow workflow that is deployed on Amazon Elastic Kubernetes Service (Amazon EKS). Define a directed acyclic graph (DAG) in which the first task is to call the Lambda function and the second task is to call the AWS Glue job.

Answer: A

Explanation:
AWS Step Functions is a service that allows you to coordinate multiple AWS services into serverless workflows. You can use Step Functions to create state machines that define the sequence and logic of the tasks in your workflow. Step Functions supports various types of tasks, such as Lambda functions, AWS Glue jobs, Amazon EMR clusters, Amazon ECS tasks, etc. You can use Step Functions to monitor and troubleshoot your workflows, as well as to handle errors and retries.
Using an AWS Step Functions workflow that includes a state machine to run the Lambda function and then the AWS Glue job will meet the requirements with the least management overhead, as it leverages the serverless and managed capabilities of Step Functions. You do not need to write any code to orchestrate the tasks in your workflow, as you can use the Step Functions console or the AWS Serverless Application Model (AWS SAM) to define and deploy your state machine. You also do not need to provision or manage any servers or clusters, as Step Functions scales automatically based on the demand.
The other options are not as efficient as using an AWS Step Functions workflow. Using an Apache Airflow workflow that is deployed on an Amazon EC2 instance or on Amazon Elastic Kubernetes Service (Amazon EKS) will require more management overhead, as you will need to provision, configure, and maintain the EC2 instance or the EKS cluster, as well as the Airflow components. You will also need to write and maintain the Airflow DAGs to orchestrate the tasks in your workflow. Using an AWS Glue workflow to run the Lambda function and then the AWS Glue job will not work, as AWS Glue workflows only support AWS Glue jobs and crawlers as tasks, not Lambda functions. References:
? AWS Step Functions
? AWS Glue
? AWS Certified Data Engineer - Associate DEA-C01 Complete Study Guide, Chapter 6: Data Integration and Transformation, Section 6.3: AWS Step Functions

NEW QUESTION 7
During a security review, a company identified a vulnerability in an AWS Glue job. The company discovered that credentials to access an Amazon Redshift cluster were hard coded in the job script.
A data engineer must remediate the security vulnerability in the AWS Glue job. The solution must securely store the credentials.
Which combination of steps should the data engineer take to meet these requirements? (Choose two.)

A. Store the credentials in the AWS Glue job parameters.
B. Store the credentials in a configuration file that is in an Amazon S3 bucket.
C. Access the credentials from a configuration file that is in an Amazon S3 bucket by using the AWS Glue job.
D. Store the credentials in AWS Secrets Manager.

E. Grant the AWS Glue job 1AM role access to the stored credentials.

Answer: DE

Explanation:
AWS Secrets Manager is a service that allows you to securely store and manage secrets, such as database credentials, API keys, passwords, etc. You can use Secrets Manager to encrypt, rotate, and audit your secrets, as well as to control access to them using fine-grained policies. AWS Glue is a fully managed service that provides a serverless data integration platform for data preparation, data cataloging, and data loading. AWS Glue jobs allow you to transform and load data from various sources into various targets, using either a graphical interface (AWS Glue Studio) or a code-based interface (AWS Glue console or AWS Glue API).
Storing the credentials in AWS Secrets Manager and granting the AWS Glue job 1AM role access to the stored credentials will meet the requirements, as it will remediate the security vulnerability in the AWS Glue job and securely store the credentials. By using AWS Secrets Manager, you can avoid hard coding the credentials in the job script, which is a bad practice that exposes the credentials to unauthorized access or leakage. Instead, you can store the credentials as a secret in Secrets Manager and reference the secret name or ARN in the job script. You can also use Secrets Manager to encrypt thecredentials using AWS Key Management Service (AWS KMS), rotate the credentials automatically or on demand, and monitor the access to the credentials using AWS CloudTrail. By granting the AWS Glue job 1AM role access to the stored credentials, you can use the principle of least privilege to ensure that only the AWS Glue job can retrieve the credentials from Secrets Manager. You can also use resource-based or tag-based policies to further restrict the access to the credentials.
The other options are not as secure as storing the credentials in AWS Secrets Manager and granting the AWS Glue job 1AM role access to the stored credentials. Storing the credentials in the AWS Glue job parameters will not remediate the security vulnerability, as the job parameters are still visible in the AWS Glue console and API. Storing the credentials in a configuration file that is in an Amazon S3 bucket and accessing the credentials from the configuration file by using the AWS Glue job will not be as secure as using Secrets Manager, as the configuration file may not be encrypted or rotated, and the access to the file may not be audited or controlled. References:
? AWS Secrets Manager
? AWS Glue
? AWS Certified Data Engineer - Associate DEA-C01 Complete Study Guide, Chapter 6: Data Integration and Transformation, Section 6.1: AWS Glue

NEW QUESTION 8
A data engineer must use AWS services to ingest a dataset into an Amazon S3 data lake. The data engineer profiles the dataset and discovers that the dataset contains personally identifiable information (PII). The data engineer must implement a solution to profile the dataset and obfuscate the PII.
Which solution will meet this requirement with the LEAST operational effort?

A. Use an Amazon Kinesis Data Firehose delivery stream to process the datase
B. Create an AWS Lambda transform function to identify the PI
C. Use an AWS SDK to obfuscate the PI
D. Set the S3 data lake as the target for the delivery stream.
E. Use the Detect PII transform in AWS Glue Studio to identify the PI
F. Obfuscate the PI
G. Use an AWS Step Functions state machine to orchestrate a data pipeline to ingest the data into the S3 data lake.
H. Use the Detect PII transform in AWS Glue Studio to identify the PI
I. Create a rule in AWS Glue Data Quality to obfuscate the PI
J. Use an AWS Step Functions state machine to orchestrate a data pipeline to ingest the data into the S3 data lake.
K. Ingest the dataset into Amazon DynamoD
L. Create an AWS Lambda function to identify and obfuscate the PII in the DynamoDB table and to transform the dat
M. Use the same Lambda function to ingest the data into the S3 data lake.

Answer: C

Explanation:
AWS Glue is a fully managed service that provides a serverless data integration platform for data preparation, data cataloging, and data loading. AWS Glue Studio is a graphical interface that allows you to easily author, run, and monitor AWS Glue ETL jobs. AWS Glue Data Quality is a feature that enables you to validate, cleanse, and enrich your data using predefined or custom rules. AWS Step Functions is a service that allows you to coordinate multiple AWS services into serverless workflows.
Using the Detect PII transform in AWS Glue Studio, you can automatically identify and label the PII in your dataset, such as names, addresses, phone numbers, email addresses, etc. You can then create a rule in AWS Glue Data Quality to obfuscate the PII, such as masking, hashing, or replacing the values with dummy data. You can also use other rules to validate and cleanse your data, such as checking for null values, duplicates, outliers, etc. You can then use an AWS Step Functions state machine to orchestrate a data pipeline to ingest the data into the S3 data lake. You can use AWS Glue DataBrew to visually explore and transform the data, AWS Glue crawlers to discover and catalog the data, and AWS Glue jobs to load the data into the S3 data lake.
This solution will meet the requirement with the least operational effort, as it leverages the serverless and managed capabilities of AWS Glue, AWS Glue Studio, AWS Glue Data Quality, and AWS Step Functions. You do not need to write any code to identify or obfuscate the PII, as you can use the built-in transforms and rules in AWS Glue Studio and AWS Glue Data Quality. You also do not need to provision or manage any servers or clusters, as AWS Glue and AWS Step Functions scale automatically based on the demand. The other options are not as efficient as using the Detect PII transform in AWS Glue Studio, creating a rule in AWS Glue Data Quality, and using an AWS Step Functions state machine. Using an Amazon Kinesis Data Firehose delivery stream to process the dataset, creating an AWS Lambda transform function to identify the PII, using an AWS SDK to obfuscate the PII, and setting the S3 data lake as the target for the delivery stream will require more operational effort, as you will need to write and maintain code to identifyand obfuscate the PII, as well as manage the Lambda function and its resources. Using the Detect PII transform in AWS Glue Studio to identify the PII, obfuscating the PII, and using an AWS Step Functions state machine to orchestrate a data pipeline to ingest the data into the S3 data lake will not be as effective as creating a rule in AWS Glue Data Quality to obfuscate the PII, as you will need to manually obfuscate the PII after identifying it, which can be error-prone and time-consuming. Ingesting the dataset into Amazon DynamoDB, creating an AWS Lambda function to identify and obfuscate the PII in the DynamoDB table and to transform the data, and using the same Lambda function to ingest the data into the S3 data lake will require more operational effort, as you will need to write and maintain code to identify and obfuscate the PII, as well as manage the Lambda function and its resources. You will also incur additional costs and complexity by using DynamoDB as an intermediate data store, which may not be necessary for your use case. References:
? AWS Glue
? AWS Glue Studio
? AWS Glue Data Quality
? [AWS Step Functions]
? [AWS Certified Data Engineer - Associate DEA-C01 Complete Study Guide], Chapter 6: Data Integration and Transformation, Section 6.1: AWS Glue

NEW QUESTION 9
A data engineer needs to create an AWS Lambda function that converts the format of data from .csv to Apache Parquet. The Lambda function must run only if a user uploads a .csv file to an Amazon S3 bucket.
Which solution will meet these requirements with the LEAST operational overhead?

A. Create an S3 event notification that has an event type of s3:ObjectCreated:*. Use a filter rule to generate notifications only when the suffix includes .cs
B. Set the Amazon Resource Name (ARN) of the Lambda function as the destination for the event notification.
C. Create an S3 event notification that has an event type of s3:ObjectTagging:* for objects that have a tag set to .cs
D. Set the Amazon Resource Name (ARN) of the Lambda function as the destination for the event notification.
E. Create an S3 event notification that has an event type of s3:*. Use a filter rule to generate notifications only when the suffix includes .cs
F. Set the Amazon Resource Name (ARN) of the Lambda function as the destination for the event notification.
G. Create an S3 event notification that has an event type of s3:ObjectCreated:*. Use a filter rule to generate notifications only when the suffix includes .cs
H. Set an Amazon Simple Notification Service (Amazon SNS) topic as the destination for the event notificatio
I. Subscribe the Lambda function to the SNS topic.

Answer: A

Explanation:
Option A is the correct answer because it meets the requirements with the least operational overhead. Creating an S3 event notification that has an event type of s3:ObjectCreated:* will trigger the Lambda function whenever a new object is created in the S3 bucket. Using a filter rule to generate notifications only when the suffix includes .csv will ensure that the Lambda function only runs for .csv files. Setting the ARN of the Lambda function as the destination for the event notification will directly invoke the Lambda function without any additional steps.
Option B is incorrect because it requires the user to tag the objects with .csv, which adds an extra step and increases the operational overhead.
Option C is incorrect because it uses an event type of s3:*, which will trigger the Lambda function for any S3 event, not just object creation. This could result in unnecessary invocations and increased costs.
Option D is incorrect because it involves creating and subscribing to an SNS topic, which adds an extra layer of complexity and operational overhead.
References:
? AWS Certified Data Engineer - Associate DEA-C01 Complete Study Guide, Chapter 3: Data Ingestion and Transformation, Section 3.2: S3 Event Notifications and Lambda Functions, Pages 67-69
? Building Batch Data Analytics Solutions on AWS, Module 4: Data Transformation, Lesson 4.2: AWS Lambda, Pages 4-8
? AWS Documentation Overview, AWS Lambda Developer Guide, Working with AWS Lambda Functions, Configuring Function Triggers, Using AWS Lambda with Amazon S3, Pages 1-5

NEW QUESTION 10
A company is migrating on-premises workloads to AWS. The company wants to reduce overall operational overhead. The company also wants to explore serverless options.
The company's current workloads use Apache Pig, Apache Oozie, Apache Spark, Apache Hbase, and Apache Flink. The on-premises workloads process petabytes of data in seconds. The company must maintain similar or better performance after the migration to AWS.
Which extract, transform, and load (ETL) service will meet these requirements?

A. AWS Glue
B. Amazon EMR
C. AWS Lambda
D. Amazon Redshift

Answer: A

Explanation:
AWS Glue is a fully managed serverless ETL service that can handle petabytes of data in seconds. AWS Glue can run Apache Spark and Apache Flink jobs without requiring any infrastructure provisioning or management. AWS Glue can also integrate with Apache Pig, Apache Oozie, and Apache Hbase using AWS Glue Data Catalog and AWS Glue workflows. AWS Glue can reduce the overall operational overhead by automating the data discovery, data preparation, and data loading processes. AWS Glue can also optimize the cost and performance of ETL jobs by using AWS Glue Job Bookmarking, AWS Glue Crawlers, and AWS Glue Schema Registry. References:
? AWS Glue
? AWS Glue Data Catalog
? AWS Glue Workflows
? [AWS Glue Job Bookmarking]
? [AWS Glue Crawlers]
? [AWS Glue Schema Registry]
? [AWS Certified Data Engineer - Associate DEA-C01 Complete Study Guide]

NEW QUESTION 10
A company has a production AWS account that runs company workloads. The company's security team created a security AWS account to store and analyze security logs from the production AWS account. The security logs in the production AWS account are stored in Amazon CloudWatch Logs.
The company needs to use Amazon Kinesis Data Streams to deliver the security logs to the security AWS account.
Which solution will meet these requirements?

A. Create a destination data stream in the production AWS accoun
B. In the security AWS account, create an IAM role that has cross-account permissions to Kinesis Data Streams in the production AWS account.
C. Create a destination data stream in the security AWS accoun
D. Create an IAM role and a trust policy to grant CloudWatch Logs the permission to put data into the strea
E. Create a subscription filter in the security AWS account.
F. Create a destination data stream in the production AWS accoun
G. In the production AWS account, create an IAM role that has cross-account permissions to Kinesis Data Streams in the security AWS account.
H. Create a destination data stream in the security AWS accoun
I. Create an IAM role and a trust policy to grant CloudWatch Logs the permission to put data into the strea
J. Create a subscription filter in the production AWS account.

Answer: D

Explanation:
Amazon Kinesis Data Streams is a service that enables you to collect, process, and analyze real-time streaming data. You can use Kinesis Data Streams to ingest data from various sources, such as Amazon CloudWatch Logs, and deliver it to different destinations, such as Amazon S3 or Amazon Redshift. To use Kinesis Data Streams to deliver the security logs from the production AWS account to the security AWS account, you need to create a destination data stream in the security AWS account. This data stream will receive the log data from the CloudWatch Logs service in the production AWS account. To enable this cross-account data delivery, you need to create an IAM role and a trust policy in the security AWS account. The IAM role defines the permissions that the CloudWatch

Logs service needs to put data into the destination data stream. The trust policy allows the production AWS account to assume the IAM role. Finally, you need to create a subscription filter in the production AWS account. A subscription filter defines the pattern to match log events and the destination to send the matching events. In this case, the destination is the destination data stream in the security AWS account. This solution meets the requirements of using Kinesis Data Streams to deliver the security logs to the security AWS account. The other options are either not possible or not optimal. You cannot create a destination data stream in the production AWS account, as this would not deliver the data to the security AWS account. You cannot create a subscription filter in the security AWS account, as this would not capture the log events from the production AWS account. References:
? Using Amazon Kinesis Data Streams with Amazon CloudWatch Logs
? AWS Certified Data Engineer - Associate DEA-C01 Complete Study Guide, Chapter 3: Data Ingestion and Transformation, Section 3.3: Amazon Kinesis Data Streams

NEW QUESTION 14
A data engineer must build an extract, transform, and load (ETL) pipeline to process and load data from 10 source systems into 10 tables that are in an Amazon Redshift database. All the source systems generate .csv, JSON, or Apache Parquet files every 15 minutes. The source systems all deliver files into one Amazon S3 bucket. The file sizes range from 10 MB to 20 GB. The ETL pipeline must function correctly despite changes to the data schema.
Which data pipeline solutions will meet these requirements? (Choose two.)

A. Use an Amazon EventBridge rule to run an AWS Glue job every 15 minute
B. Configure the AWS Glue job to process and load the data into the Amazon Redshift tables.
C. Use an Amazon EventBridge rule to invoke an AWS Glue workflow job every 15 minute
D. Configure the AWS Glue workflow to have an on-demand trigger that runs an AWS Glue crawler and then runs an AWS Glue job when the crawler finishes running successfull
E. Configure the AWS Glue job to process and load the data into the Amazon Redshift tables.
F. Configure an AWS Lambda function to invoke an AWS Glue crawler when a file is loaded into the S3 bucke
G. Configure an AWS Glue job to process and load the data into the Amazon Redshift table
H. Create a second Lambda function to run the AWS Glue jo
I. Create an Amazon EventBridge rule to invoke the second Lambda function when the AWS Glue crawler finishes running successfully.
J. Configure an AWS Lambda function to invoke an AWS Glue workflow when a file is loaded into the S3 bucke
K. Configure the AWS Glue workflow to have an on-demand trigger that runs an AWS Glue crawler and then runs an AWS Glue job when the crawler finishes running successfull
L. Configure the AWS Glue job to process and load the data into the Amazon Redshift tables.
M. Configure an AWS Lambda function to invoke an AWS Glue job when a file is loaded into the S3 bucke
N. Configure the AWS Glue job to read the files from the S3 bucket into an Apache Spark DataFram
O. Configure the AWS Glue job to also put smaller partitions of the DataFrame into an Amazon Kinesis Data Firehose delivery strea
P. Configure the delivery stream to load data into the Amazon Redshift tables.

Answer: AB

Explanation:
Using an Amazon EventBridge rule to run an AWS Glue job or invoke an AWS Glue workflow job every 15 minutes are two possible solutions that will meet the requirements. AWS Glue is a serverless ETL service that can process and load data from various sources to various targets, including Amazon Redshift. AWS Glue can handle different data formats, such as CSV, JSON, and Parquet, and also support schema evolution, meaning it can adapt to changes in the data schema over time. AWS Glue can also leverage Apache Spark to perform distributed processing and transformation of large datasets. AWS Glue integrates with Amazon EventBridge, which is a serverless event bus service that can trigger actions based on rules and schedules. By using an Amazon EventBridge rule, you can invoke an AWS Glue job or workflow every 15 minutes, and configure the job or workflow to run an AWS Glue crawler and then load the data into the Amazon Redshift tables. This way, you can build a cost-effective and scalable ETL pipeline that can handle data from 10 source systems and function correctly despite changes to the data schema.
The other options are not solutions that will meet the requirements. Option C, configuring an AWS Lambda function to invoke an AWS Glue crawler when a file is loaded into the S3 bucket, and creating a second Lambda function to run the AWS Glue job, is not a feasible solution, as it would require a lot of Lambda invocations andcoordination. AWS Lambda has some limits on the execution time, memory, and concurrency, which can affect the performance and reliability of the ETL pipeline. Option D, configuring an AWS Lambda function to invoke an AWS Glue workflow when a file is loaded into the S3 bucket, is not a necessary solution, as you can use an Amazon EventBridge rule to invoke the AWS Glue workflow directly, without the need for a Lambda function. Option E, configuring an AWS Lambda function to invoke an AWS Glue job when a file is loaded into the S3 bucket, and configuring the AWS Glue job to put smaller partitions of the DataFrame into an Amazon Kinesis Data Firehose delivery stream, is not a cost-effective solution, as it would incur additional costs for Lambda invocations and data delivery. Moreover, using Amazon Kinesis Data Firehose to load data into Amazon Redshift is not suitable for frequent and small batches of data, as it can cause performance issues and data fragmentation. References:
? AWS Glue
? Amazon EventBridge
? Using AWS Glue to run ETL jobs against non-native JDBC data sources
? [AWS Lambda quotas]
? [Amazon Kinesis Data Firehose quotas]

NEW QUESTION 15
A financial company wants to use Amazon Athena to run on-demand SQL queries on a petabyte-scale dataset to support a business intelligence (BI) application. An AWS Glue job that runs during non-business hours updates the dataset once every day. The BI application has a standard data refresh frequency of 1 hour to comply with company policies.
A data engineer wants to cost optimize the company's use of Amazon Athena without adding any additional infrastructure costs.
Which solution will meet these requirements with the LEAST operational overhead?

A. Configure an Amazon S3 Lifecycle policy to move data to the S3 Glacier Deep Archive storage class after 1 day
B. Use the query result reuse feature of Amazon Athena for the SQL queries.
C. Add an Amazon ElastiCache cluster between the Bl application and Athena.
D. Change the format of the files that are in the dataset to Apache Parquet.

Answer: B

Explanation:
The best solution to cost optimize the company’s use of Amazon Athena without adding any additional infrastructure costs is to use the query result reuse feature of AmazonAthena for the SQL queries. This feature allows you to run the same query multiple times without incurring additional charges, as long as the underlying data has not changed and the query results are still in the query result location in Amazon S31. This feature is useful for scenarios where you have a petabyte-scale dataset that is updated infrequently, such as once a day, and you have a BI application that runs the same queries repeatedly, such as every hour. By using the query result reuse feature, you can reduce the amount of data scanned by your queries and save on the cost of running Athena. You can enable or disable this

feature at the workgroup level or at the individual query level1.
Option A is not the best solution, as configuring an Amazon S3 Lifecycle policy to move data to the S3 Glacier Deep Archive storage class after 1 day would not cost optimize the company's use of Amazon Athena, but rather increase the cost and complexity. Amazon S3 Lifecycle policies are rules that you can define to automatically transition objects between different storage classes based on specified criteria, such as the age of the object2. S3 Glacier Deep Archive is the lowest-cost storage class in Amazon S3, designed
for long-term data archiving that is accessed once or twice in a year3. While moving data to S3 Glacier Deep Archive can reduce the storage cost, it would also increase the retrieval cost and latency, as it takes up to 12 hours to restore the data from S3 Glacier Deep Archive3. Moreover, Athena does not support querying data that is in S3 Glacier or S3 Glacier Deep Archive storage classes4. Therefore, using this option would not meet the requirements of running on-demand SQL queries on the dataset.
Option C is not the best solution, as adding an Amazon ElastiCache cluster between the BI application and Athena would not cost optimize the company's use of Amazon Athena, but rather increase the cost and complexity. Amazon ElastiCache is a service that offers fully managed in-memory data stores, such as Redis and Memcached, that can improve the performance and scalability of web applications by caching frequently accessed data. While using ElastiCache can reduce the latency and load on the BI application, it would not reduce the amount of data scanned by Athena, which is the main factor that determines the cost of running Athena. Moreover, using ElastiCache would introduce additional infrastructure costs and operational overhead, as you would have to provision, manage, and scale the ElastiCache cluster, and integrate it with the BI application and Athena. Option D is not the best solution, as changing the format of the files that are in the dataset to Apache Parquet would not cost optimize the company's use of Amazon Athena without adding any additional infrastructure costs, but rather increase the complexity. Apache Parquet is a columnar storage format that can improve the performance of analytical queries by reducing the amount of data that needs to be scanned and providing efficient compression and encoding schemes. However,changing the format of the files that are in the dataset to Apache Parquet would require additional processing and transformation steps, such as using AWS Glue or Amazon EMR to convert the files from their original format to Parquet, and storing the converted files in a separate location in Amazon S3. This would increase the complexity and the operational overhead of the data pipeline, and also incur additional costs for using AWS Glue or Amazon EMR. References:
? Query result reuse
? Amazon S3 Lifecycle
? S3 Glacier Deep Archive
? Storage classes supported by Athena
? [What is Amazon ElastiCache?]
? [Amazon Athena pricing]
? [Columnar Storage Formats]
? AWS Certified Data Engineer - Associate DEA-C01 Complete Study Guide

NEW QUESTION 19
A data engineer must ingest a source of structured data that is in .csv format into an Amazon S3 data lake. The .csv files contain 15 columns. Data analysts need to run Amazon Athena queries on one or two columns of the dataset. The data analysts rarely query the entire file.
Which solution will meet these requirements MOST cost-effectively?

A. Use an AWS Glue PySpark job to ingest the source data into the data lake in .csv format.
B. Create an AWS Glue extract, transform, and load (ETL) job to read from the .csv structured data sourc
C. Configure the job to ingest the data into the data lake in JSON format.
D. Use an AWS Glue PySpark job to ingest the source data into the data lake in Apache Avro format.
E. Create an AWS Glue extract, transform, and load (ETL) job to read from the .csv structured data sourc
F. Configure the job to write the data into the data lake in Apache Parquet format.

Answer: D

Explanation:
Amazon Athena is a serverless interactive query service that allows you to analyze data in Amazon S3 using standard SQL. Athena supports various data formats, such as CSV,JSON, ORC, Avro, and Parquet. However, not all data formats are equally efficient for querying. Some data formats, such as CSV and JSON, are row-oriented, meaning that they store data as a sequence of records, each with the same fields. Row- oriented formats are suitable for loading and exporting data, but they are not optimal for analytical queries that often access only a subset of columns. Row-oriented formats also do not support compression or encoding techniques that can reduce the data size and improve the query performance.
On the other hand, some data formats, such as ORC and Parquet, are column-oriented, meaning that they store data as a collection of columns, each with a specific data type. Column-oriented formats are ideal for analytical queries that often filter, aggregate, or join data by columns. Column-oriented formats also support compression and encoding techniques that can reduce the data size and improve the query performance. For example, Parquet supports dictionary encoding, which replaces repeated values with numeric codes, and run-length encoding, which replaces consecutive identical values with a single value and a count. Parquet also supports various compression algorithms, such as Snappy, GZIP, and ZSTD, that can further reduce the data size and improve the query performance.
Therefore, creating an AWS Glue extract, transform, and load (ETL) job to read from the .csv structured data source and writing the data into the data lake in Apache Parquet format will meet the requirements most cost-effectively. AWS Glue is a fully managed service that provides a serverless data integration platform for data preparation, data cataloging, and data loading. AWS Glue ETL jobs allow you to transform and load data from various sources into various targets, using either a graphical interface (AWS Glue Studio) or a code-based interface (AWS Glue console or AWS Glue API). By using AWS Glue ETL jobs, you can easily convert the data from CSV to Parquet format, without having to write or manage any code. Parquet is a column-oriented format that allows Athena to scan only the relevant columns and skip the rest, reducing the amount of data read from S3. This solution will also reduce the cost of Athena queries, as Athena charges based on the amount of data scanned from S3.
The other options are not as cost-effective as creating an AWS Glue ETL job to write the data into the data lake in Parquet format. Using an AWS Glue PySpark job to ingest the source data into the data lake in .csv format will not improve the query performance or reduce the query cost, as .csv is a row-oriented format that does not support columnar access or compression. Creating an AWS Glue ETL job to ingest the data into the data lake in JSON format will not improve the query performance or reduce the query cost, as JSON is also a row-oriented format that does not support columnar access or compression. Using an AWS Glue PySpark job to ingest the source data into the data lake in Apache Avro format will improve the query performance, as Avro is a column-oriented format that supports compression and encoding, but it will require more operational effort, as you will need to write and maintain PySpark code to convert the data from CSV to Avro format. References:
? Amazon Athena
? Choosing the Right Data Format
? AWS Glue
? [AWS Certified Data Engineer - Associate DEA-C01 Complete Study Guide], Chapter 5: Data Analysis and Visualization, Section 5.1: Amazon Athena

NEW QUESTION 20
A company needs to build a data lake in AWS. The company must provide row-level data access and column-level data access to specific teams. The teams will access the data by using Amazon Athena, Amazon Redshift Spectrum, and Apache Hive from Amazon EMR.
Which solution will meet these requirements with the LEAST operational overhead?

A. Use Amazon S3 for data lake storag

B. Use S3 access policies to restrict data access by rows and column
C. Provide data access throughAmazon S3.
D. Use Amazon S3 for data lake storag
E. Use Apache Ranger through Amazon EMR to restrict data access byrows and column
F. Providedata access by using Apache Pig.
G. Use Amazon Redshift for data lake storag
H. Use Redshift security policies to restrict data access byrows and column
I. Provide data accessby usingApache Spark and Amazon Athena federated queries.
J. UseAmazon S3 for data lake storag
K. Use AWS Lake Formation to restrict data access by rows and column
L. Provide data access through AWS Lake Formation.

Answer: D

Explanation:
Option D is the best solution to meet the requirements with the least operational overhead because AWS Lake Formation is a fully managed service that simplifies the process of building, securing, and managing data lakes. AWS Lake Formation allows you to define granular data access policies at the row and column level for different users and groups. AWS Lake Formation also integrates with Amazon Athena, Amazon Redshift Spectrum, and Apache Hive on Amazon EMR, enabling these services to access the data in the data lake through AWS Lake Formation.
Option A is not a good solution because S3 access policies cannot restrict data access by rows and columns. S3 access policies are based on the identity and permissions of the requester, the bucket and object ownership, and the object prefix and tags. S3 access policies cannot enforce fine-grained data access control at the row and column level. Option B is not a good solution because it involves using Apache Ranger and Apache Pig, which are not fully managed services and require additional configuration and maintenance. Apache Ranger is a framework that provides centralized security administration for data stored in Hadoop clusters, such as Amazon EMR. Apache Ranger can enforce row-level and column-level access policies for Apache Hive tables. However, Apache Ranger is not a native AWS service and requires manual installation and configuration on Amazon EMR clusters. Apache Pig is a platform that allows you to analyze large data sets using a high-level scripting language called Pig Latin. Apache Pig can access data stored in Amazon S3 and process it using Apache Hive. However,Apache Pig is not a native AWS service and requires manual installation and configuration on Amazon EMR clusters.
Option C is not a good solution because Amazon Redshift is not a suitable service for data lake storage. Amazon Redshift is a fully managed data warehouse service that allows you to run complex analytical queries using standard SQL. Amazon Redshift can enforce row- level and column-level access policies for different users and groups. However, Amazon Redshift is not designed to store and process large volumes of unstructured or semi- structured data, which are typical characteristics of data lakes. Amazon Redshift is also more expensive and less scalable than Amazon S3 for data lake storage.
References:
? AWS Certified Data Engineer - Associate DEA-C01 Complete Study Guide
? What Is AWS Lake Formation? - AWS Lake Formation
? Using AWS Lake Formation with Amazon Athena - AWS Lake Formation
? Using AWS Lake Formation with Amazon Redshift Spectrum - AWS Lake Formation
? Using AWS Lake Formation with Apache Hive on Amazon EMR - AWS Lake Formation
? Using Bucket Policies and User Policies - Amazon Simple Storage Service
? Apache Ranger
? Apache Pig
? What Is Amazon Redshift? - Amazon Redshift

NEW QUESTION 24
A company is migrating a legacy application to an Amazon S3 based data lake. A data engineer reviewed data that is associated with the legacy application. The data engineer found that the legacy data contained some duplicate information.
The data engineer must identify and remove duplicate information from the legacy application data.
Which solution will meet these requirements with the LEAST operational overhead?

A. Write a custom extract, transform, and load (ETL) job in Pytho
B. Use the DataFramedrop duplicatesf) function by importingthe Pandas library to perform data deduplication.
C. Write an AWS Glue extract, transform, and load (ETL) jo
D. Usethe FindMatches machine learning(ML) transform to transform the data to perform data deduplication.
E. Write a custom extract, transform, and load (ETL) job in Pytho
F. Import the Python dedupe librar
G. Use the dedupe library to perform data deduplication.
H. Write an AWS Glue extract, transform, and load (ETL) jo
I. Import the Python dedupe librar
J. Use the dedupe library to perform data deduplication.

Answer: B

Explanation:
AWS Glue is a fully managed serverless ETL service that can handle data deduplication with minimal operational overhead. AWS Glue provides a built-in ML transform called FindMatches, which can automatically identify and group similar records in a dataset. FindMatches can also generate a primary key for each group of records and remove duplicates. FindMatches does not require any coding or prior ML experience, as it can learn from a sample of labeled data provided by the user. FindMatches can also scale to handle large datasets and optimize the cost and performance of the ETL job. References:
? AWS Glue
? FindMatches ML Transform
? AWS Certified Data Engineer - Associate DEA-C01 Complete Study Guide

NEW QUESTION 29
A company uses Amazon RDS to store transactional data. The company runs an RDS DB instance in a private subnet. A developer wrote an AWS Lambda function with default settings to insert, update, or delete data in the DB instance.
The developer needs to give the Lambda function the ability to connect to the DB instance privately without using the public internet.
Which combination of steps will meet this requirement with the LEAST operational overhead? (Choose two.)

A. Turn on the public access setting for the DB instance.
B. Update the security group of the DB instance to allow only Lambda function invocations on the database port.
C. Configure the Lambda function to run in the same subnet that the DB instance uses.
D. Attach the same security group to the Lambda function and the DB instanc
E. Include a self-referencing rule that allows access through the database port.

F. Update the network ACL of the private subnet to include a self-referencing rule that allows access through the database port.

Answer: CD

Explanation:
To enable the Lambda function to connect to the RDS DB instance privately without using the public internet, the best combination of steps is to configure the Lambda function to run in the same subnet that the DB instance uses, and attach the same security group to the Lambda function and the DB instance. This way, the Lambda function and the DB instance can communicate within the same private network, and the security group can allow traffic between them on the database port. This solution has the least operational overhead, as it does not require any changes to the public access setting, the network ACL, or the security group of the DB instance.
The other options are not optimal for the following reasons:
? A. Turn on the public access setting for the DB instance. This option is not recommended, as it would expose the DB instance to the public internet, which can compromise the security and privacy of the data. Moreover, this option would not enable the Lambda function to connect to the DB instance privately, as it would still require the Lambda function to use the public internet to access the DB instance.
? B. Update the security group of the DB instance to allow only Lambda function invocations on the database port. This option is not sufficient, as it would only modify the inbound rules of the security group of the DB instance, but not the outbound rules of the security group of the Lambda function. Moreover, this option would not enable the Lambda function to connect to the DB instance privately, as it would still require the Lambda function to use the public internet to access the DB instance.
? E. Update the network ACL of the private subnet to include a self-referencing rule
that allows access through the database port. This option is not necessary, as the network ACL of the private subnet already allows all traffic within the subnet by default. Moreover, this option would not enable the Lambda function to connect to the DB instance privately, as it would still require the Lambda function to use the public internet to access the DB instance.
References:
? 1: Connecting to an Amazon RDS DB instance
? 2: Configuring a Lambda function to access resources in a VPC
? 3: Working with security groups
? : Network ACLs

NEW QUESTION 31
A company has multiple applications that use datasets that are stored in an Amazon S3 bucket. The company has an ecommerce application that generates a dataset that contains personally identifiable information (PII). The company has an internal analytics application that does not require access to the PII.
To comply with regulations, the company must not share PII unnecessarily. A data engineer needs to implement a solution that with redact PII dynamically, based on the needs of each application that accesses the dataset.
Which solution will meet the requirements with the LEAST operational overhead?

A. Create an S3 bucket policy to limit the access each application ha
B. Create multiple copies of the datase
C. Give each dataset copy the appropriate level of redaction for the needs of the application that accesses the copy.
D. Create an S3 Object Lambda endpoin
E. Use the S3 Object Lambda endpoint to read data from the S3 bucke
F. Implement redaction logic within an S3 Object Lambda function to dynamically redact PII based on the needs of each application that accesses the data.
G. Use AWS Glue to transform the data for each applicatio
H. Create multiple copies of the datase
I. Give each dataset copy the appropriate level of redaction for the needs of the application that accesses the copy.
J. Create an API Gateway endpoint that has custom authorizer
K. Use the API Gateway endpoint to read data from the S3 bucke
L. Initiate a REST API call to dynamically redact PII based on the needs of each application that accesses the data.

Answer: B

Explanation:
Option B is the best solution to meet the requirements with the least operational overhead because S3 Object Lambda is a feature that allows you to add your own code to process data retrieved from S3 before returning it to an application. S3 Object Lambda works with S3 GET requests and can modify both the object metadata and the object data. By using S3 Object Lambda, you can implement redaction logic within an S3 Object Lambda function to dynamically redact PII based on the needs of each application that accesses the data. This way, you can avoid creating and maintaining multiple copies of the dataset with different levels of redaction.
Option A is not a good solution because it involves creating and managing multiple copies of the dataset with different levels of redaction for each application. This option adds complexity and storage cost to the data protection process and requires additional resources and configuration. Moreover, S3 bucket policies cannot enforce fine-grained data access control at the row and column level, so they are not sufficient to redact PII.
Option C is not a good solution because it involves using AWS Glue to transform the data for each application. AWS Glue is a fully managed service that can extract, transform, and load (ETL) data from various sources to various destinations, including S3. AWS Glue can also convert data to different formats, such as Parquet, which is a columnar storage format that is optimized for analytics. However, in this scenario, using AWS Glue to redact PII is not the best option because it requires creating and maintaining multiple copies of the dataset with different levels of redaction for each application. This option also adds extra time and cost to the data protection process and requires additional resources and configuration.
Option D is not a good solution because it involves creating and configuring an API Gateway endpoint that has custom authorizers. API Gateway is a service that allows youto create, publish, maintain, monitor, and secure APIs at any scale. API Gateway can also integrate with other AWS services, such as Lambda, to provide custom logic for processing requests. However, in this scenario, using API Gateway to redact PII is not the best option because it requires writing and maintaining custom code and configuration for the API endpoint, the custom authorizers, and the REST API call. This option also adds complexity and latency to the data protection process and requires additional resources and configuration.
References:
? AWS Certified Data Engineer - Associate DEA-C01 Complete Study Guide
? Introducing Amazon S3 Object Lambda – Use Your Code to Process Data as It Is Being Retrieved from S3
? Using Bucket Policies and User Policies - Amazon Simple Storage Service
? AWS Glue Documentation
? What is Amazon API Gateway? - Amazon API Gateway

NEW QUESTION 36
A data engineer has a one-time task to read data from objects that are in Apache Parquet format in an Amazon S3 bucket. The data engineer needs to query only one column of the data.
Which solution will meet these requirements with the LEAST operational overhead?

A. Confiqure an AWS Lambda function to load data from the S3 bucket into a pandas dataframe- Write a SQL SELECT statement on the dataframe to query the required column.
B. Use S3 Select to write a SQL SELECT statement to retrieve the required column from the S3 objects.
C. Prepare an AWS Glue DataBrew project to consume the S3 objects and to query the required column.
D. Run an AWS Glue crawler on the S3 object
E. Use a SQL SELECT statement in Amazon Athena to query the required column.

Answer: B

Explanation:
Option B is the best solution to meet the requirements with the least operational overhead because S3 Select is a feature that allows you to retrieve only a subset of data from an S3 object by using simple SQL expressions. S3 Select works on objects stored in CSV, JSON, or Parquet format. By using S3 Select, you can avoid the need to download and process the entire S3 object, which reduces the amount of data transferred and the computation time. S3 Select is also easy to use and does not require any additional services or resources.
Option A is not a good solution because it involves writing custom code and configuring an AWS Lambda function to load data from the S3 bucket into a pandas dataframe and query the required column. This option adds complexity and latency to the data retrieval process and requires additional resources and configuration.Moreover, AWS Lambda has limitations on the execution time, memory, and concurrency, which may affect the performance and reliability of the data retrieval process.
Option C is not a good solution because it involves creating and running an AWS Glue DataBrew project to consume the S3 objects and query the required column. AWS Glue DataBrew is a visual data preparation tool that allows you to clean, normalize, and transform data without writing code. However, in this scenario, the data is already in Parquet format, which is a columnar storage format that is optimized for analytics. Therefore, there is no need to use AWS Glue DataBrew to prepare the data. Moreover, AWS Glue DataBrew adds extra time and cost to the data retrieval process and requires additional resources and configuration.
Option D is not a good solution because it involves running an AWS Glue crawler on the S3 objects and using a SQL SELECT statement in Amazon Athena to query the required column. An AWS Glue crawler is a service that can scan data sources and create metadata tables in the AWS Glue Data Catalog. The Data Catalog is a central repository that stores information about the data sources, such as schema, format, and location. Amazon Athena is a serverless interactive query service that allows you to analyze data in S3 using standard SQL. However, in this scenario, the schema and format of the data are already known and fixed, so there is no need to run a crawler to discover them. Moreover, running a crawler and using Amazon Athena adds extra time and cost to the data retrieval process and requires additional services and configuration.
References:
? AWS Certified Data Engineer - Associate DEA-C01 Complete Study Guide
? S3 Select and Glacier Select - Amazon Simple Storage Service
? AWS Lambda - FAQs
? What Is AWS Glue DataBrew? - AWS Glue DataBrew
? Populating the AWS Glue Data Catalog - AWS Glue
? What is Amazon Athena? - Amazon Athena

NEW QUESTION 37
A data engineer needs to securely transfer 5 TB of data from an on-premises data center to an Amazon S3 bucket. Approximately 5% of the data changes every day. Updates to the data need to be regularlyproliferated to the S3 bucket. The data includes files that are in multiple formats. The data engineer needs to automate the transfer process and must schedule the process to run periodically.
Which AWS service should the data engineer use to transfer the data in the MOST operationally efficient way?

A. AWS DataSync
B. AWS Glue
C. AWS Direct Connect
D. Amazon S3 Transfer Acceleration

Answer: A

Explanation:
AWS DataSync is an online data movement and discovery service that simplifies and accelerates data migrations to AWS as well as moving data to and from on-premises storage, edge locations, other cloud providers, and AWS Storage services1. AWS DataSync can copy data to and from various sources and targets, including Amazon S3, and handle files in multiple formats. AWS DataSync also supports incremental transfers, meaning it can detect and copy only the changes to the data, reducing the amount of data transferred and improving the performance. AWS DataSync can automate and schedule the transfer process using triggers, and monitor the progress and status of the transfers using CloudWatch metrics and events1.
AWS DataSync is the most operationally efficient way to transfer the data in this scenario, as it meets all the requirements and offers a serverless and scalable solution. AWS Glue, AWS Direct Connect, and Amazon S3 Transfer Acceleration are not the best options for this scenario, as they have some limitations or drawbacks compared to AWS DataSync. AWS Glue is a serverless ETL service that can extract, transform, and load data from various sources to various targets, including Amazon S32. However, AWS Glue is not designed for large-scale data transfers, as it has some quotas and limits on the number and size of files it can process3. AWS Glue also does not support incremental transfers, meaning it would have to copy the entire data set every time, which would be inefficient and costly.
AWS Direct Connect is a service that establishes a dedicated network connection between your on-premises data center and AWS, bypassing the public internet and improving the bandwidth and performance of the data transfer. However, AWS Direct Connect is not a data transfer service by itself, as it requires additional services or tools to copy the data, such as AWS DataSync, AWS Storage Gateway, or AWS CLI. AWS Direct Connect also has some hardware and location requirements, and charges you for the port hours and data transfer out of AWS.
Amazon S3 Transfer Acceleration is a feature that enables faster data transfers to Amazon S3 over long distances, using the AWS edge locations and optimized network paths. However, Amazon S3 Transfer Acceleration is not a data transfer service by itself, as it requires additional services or tools to copy the data, such as AWS CLI, AWS SDK, or third-party software. Amazon S3 Transfer Acceleration also charges you for the data transferred over the accelerated endpoints, and does not guarantee a performance improvement for every transfer, as it depends on various factors such as the network conditions, the distance, and the object size. References:
? AWS DataSync
? AWS Glue
? AWS Glue quotas and limits
? [AWS Direct Connect]
? [Data transfer options for AWS Direct Connect]
? [Amazon S3 Transfer Acceleration]
? [Using Amazon S3 Transfer Acceleration]

NEW QUESTION 42
A company is planning to use a provisioned Amazon EMR cluster that runs Apache Spark jobs to perform big data analysis. The company requires high reliability.

A big data team must follow best practices for running cost-optimized and long-running workloads on Amazon EMR. The team must find a solution that will maintain the company's current level of performance.
Which combination of resources will meet these requirements MOST cost-effectively? (Choose two.)

A. Use Hadoop Distributed File System (HDFS) as a persistent data store.
B. Use Amazon S3 as a persistent data store.
C. Use x86-based instances for core nodes and task nodes.
D. Use Graviton instances for core nodes and task nodes.
E. Use Spot Instances for all primary nodes.

Answer: BD

Explanation:
The best combination of resources to meet the requirements of high reliability, cost-optimization, and performance for running Apache Spark jobs on Amazon EMR is to use Amazon S3 as a persistent data store and Graviton instances for core nodes and task nodes.
Amazon S3 is a highly durable, scalable, and secure object storage service that can store any amount of data for a variety of use cases, including big data analytics1. Amazon S3 is a better choice than HDFS as a persistent data store for Amazon EMR, as it decouples the storage from the compute layer, allowing for more flexibility and cost-efficiency. Amazon S3 also supports data encryption, versioning, lifecycle management, and cross-region replication1. Amazon EMR integrates seamlessly with Amazon S3, using EMR File System (EMRFS) to access data stored in Amazon S3 buckets2. EMRFS also supports consistent view, which enables Amazon EMR to provide read-after-write consistency for Amazon S3 objects that are accessed through EMRFS2.
Graviton instances are powered by Arm-based AWS Graviton2 processors that deliver up to 40% better price performance over comparable current generation x86-based instances3. Graviton instances are ideal for running workloads that are CPU-bound, memory-bound, or network-bound, such as big data analytics, web servers, and open- source databases3. Graviton instances are compatible with Amazon EMR, and can beused for both core nodes and task nodes. Core nodes are responsible for running the data processing frameworks, such as Apache Spark, and storing data in HDFS or the local file system. Task nodes are optional nodes that can be added to a cluster to increase the processing power and throughput. By using Graviton instances for both core nodes and task nodes, you can achieve higher performance and lower cost than using x86-based instances.
Using Spot Instances for all primary nodes is not a good option, as it can compromise the reliability and availability of the cluster. Spot Instances are spare EC2 instances that are available at up to 90% discount compared to On-Demand prices, but they can be interrupted by EC2 with a two-minute notice when EC2 needs the capacity back. Primary nodes are the nodes that run the cluster software, such as Hadoop, Spark, Hive, and Hue, and are essential for the cluster operation. If a primary node is interrupted by EC2, the cluster will fail or become unstable. Therefore, it is recommended to use On-Demand Instances or Reserved Instances for primary nodes, and use Spot Instances only for task nodes that can tolerate interruptions. References:
? Amazon S3 - Cloud Object Storage
? EMR File System (EMRFS)
? AWS Graviton2 Processor-Powered Amazon EC2 Instances
? [Plan and Configure EC2 Instances]
? [Amazon EC2 Spot Instances]
? [Best Practices for Amazon EMR]

NEW QUESTION 44
A company stores data in a data lake that is in Amazon S3. Some data that the company stores in the data lake contains personally identifiable information (PII). Multiple user groups need to access the raw data. The company must ensure that user groups can access only the PII that they require.
Which solution will meet these requirements with the LEAST effort?

A. Use Amazon Athena to query the dat
B. Set up AWS Lake Formation and create data filters to establish levels of access for the company's IAM role
C. Assign each user to the IAM role that matches the user's PII access requirements.
D. Use Amazon QuickSight to access the dat
E. Use column-level security features in QuickSight to limit the PII that users can retrieve from Amazon S3 by using Amazon Athen
F. Define QuickSight access levels based on the PII access requirements of the users.
G. Build a custom query builder UI that will run Athena queries in the background to access the dat
H. Create user groups in Amazon Cognit
I. Assign access levels to the user groups based on the PII access requirements of the users.
J. Create IAM roles that have different levels of granular acces
K. Assign the IAM roles to IAM user group
L. Use an identity-based policy to assign access levels to user groups at the column level.

Answer: A

Explanation:
Amazon Athena is a serverless, interactive query service that enables you to analyze data in Amazon S3 using standard SQL. AWS Lake Formation is a service that helps you build, secure, and manage data lakes on AWS. You can use AWS Lake Formation to create data filters that define the level of access for different IAM roles based on the columns, rows, or tags of the data. By using Amazon Athena to query the data and AWS Lake Formation to create data filters, the company can meet the requirements of ensuring that user groups can access only the PII that they require with the least effort. The solution is to use Amazon Athena to query the data in the data lake that is in Amazon S3. Then, set up AWS Lake Formation and create data filters to establish levels of access for the company's IAM roles. For example, a data filter can allow a user group to access only the columns that contain the PII that they need, such as name and email address, and deny access to the columns that contain the PII that they do not need, such as phone number and social security number. Finally, assign each user to the IAM role that matches the user's PII access requirements. This way, the user groups can access the data in the data lake securely and efficiently. The other options are either not feasible or not optimal. Using Amazon QuickSight to access the data (option B) would require the company to pay for the QuickSight service and to configure the column-level security features for each user. Building a custom query builder UI that will run Athena queries in the background to access the data (option C) would require the company to develop and maintain the UI and to integrate it with Amazon Cognito. Creating IAM roles that have different levels of granular access (option D) would require the company to manage multiple IAM roles and policies and to ensure that they are aligned with the data schema.
References:
? Amazon Athena
? AWS Lake Formation
? AWS Certified Data Engineer - Associate DEA-C01 Complete Study Guide, Chapter 4: Data Analysis and Visualization, Section 4.3: Amazon Athena

NEW QUESTION 49
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