Group Project - AWS Data Analytic Platform for The City of Vancouver

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BUSI653: Cloud Computing Technologies (HBD-WINTER25-03)

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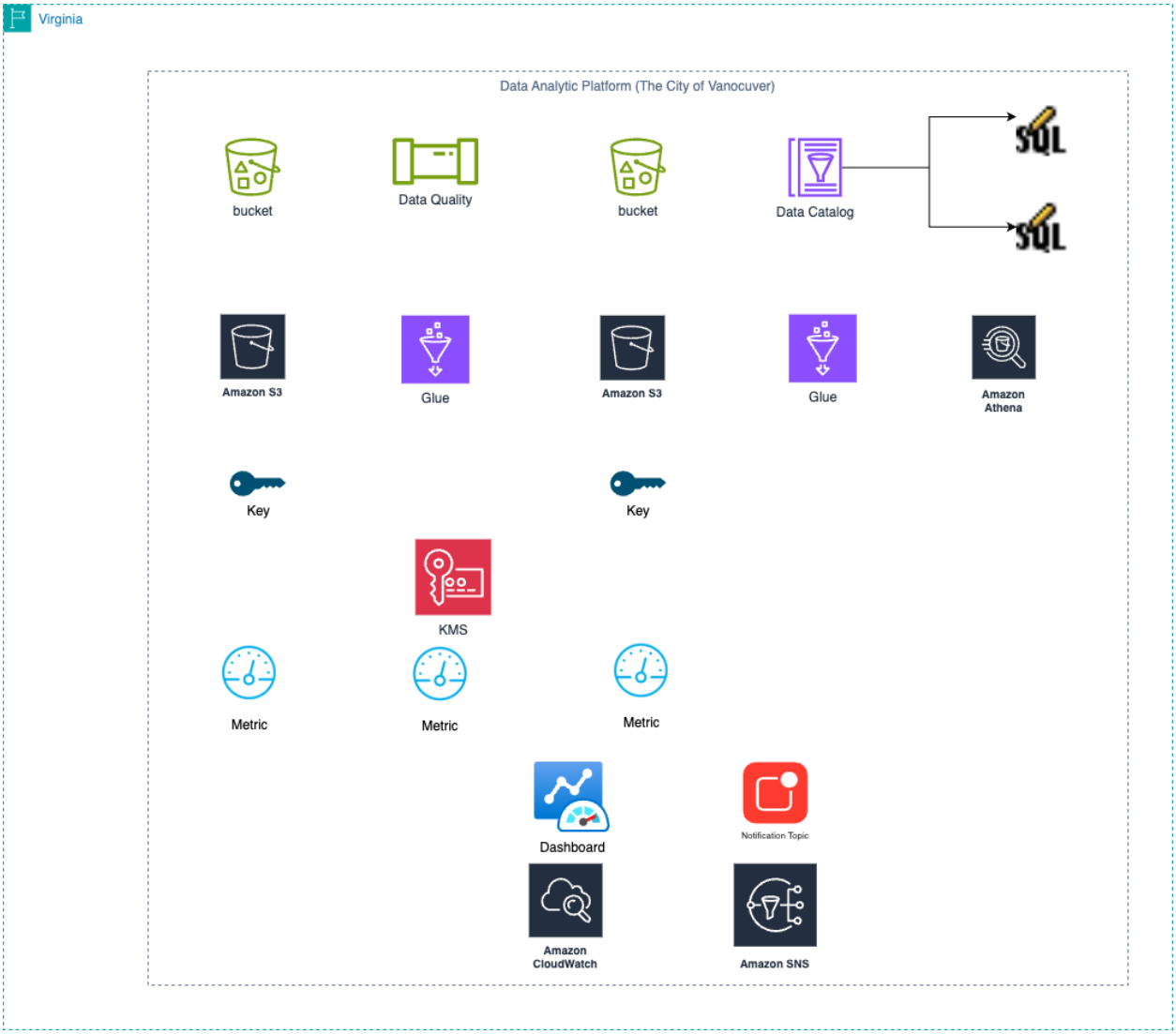
Figure 1

DAP requirements for the City of Vancouver



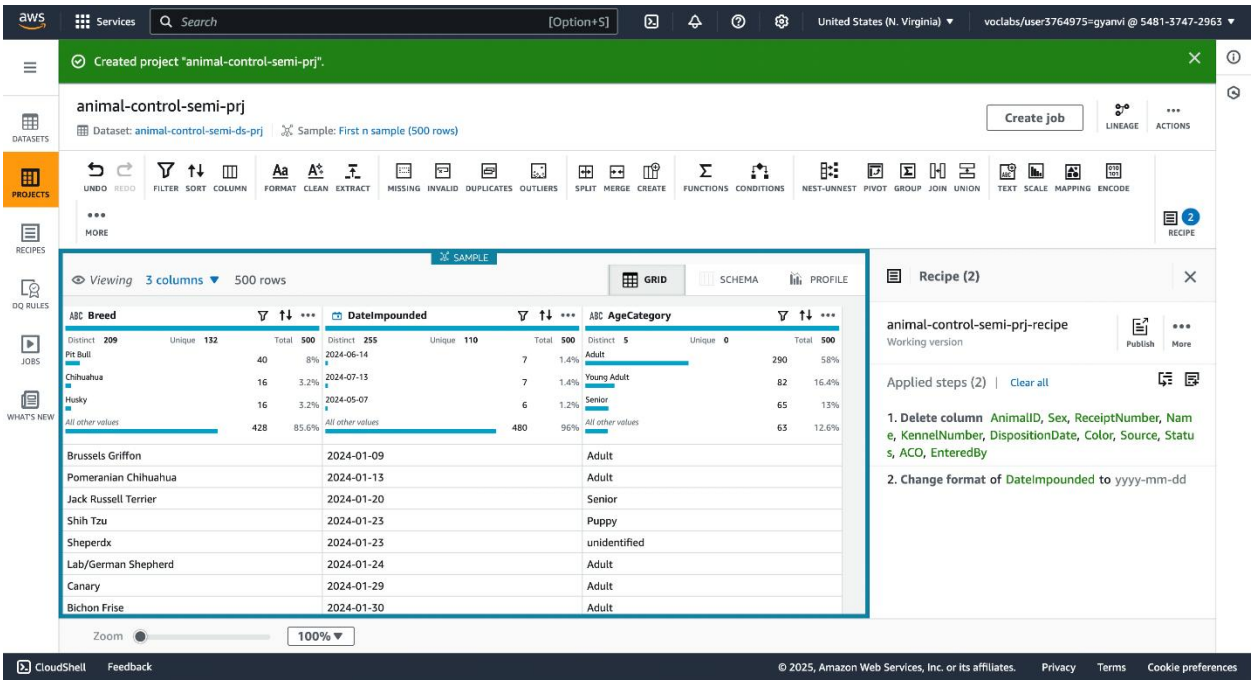
Note. This picture shows the procedure our team needs to implement the DAP to support the requirements of the City of Vancouver *(Draw.io, self-work).*

DAP Implementation (Individual work - Gyanvi Bhardwaj)

Step 5: Data Analysis

The data analysis step was carried out using AWS Athena which employs SQL queries to analyze data. A new folder was created in the raw zone of the AWS S3 bucket and named 'animal-control-semi-ds'. This contained the cleaned dataset. Using Glue Databrew, the columns that were not required to answer the two business questions were dropped. This also ensures that the cost associated with scanning the data is lowered as only the required data is available in the dataset provided for analysis to Athena. Now, the dataset is structured and ready for analysis using Athena.

Figure 2: Cleaned dataset ready for analysis

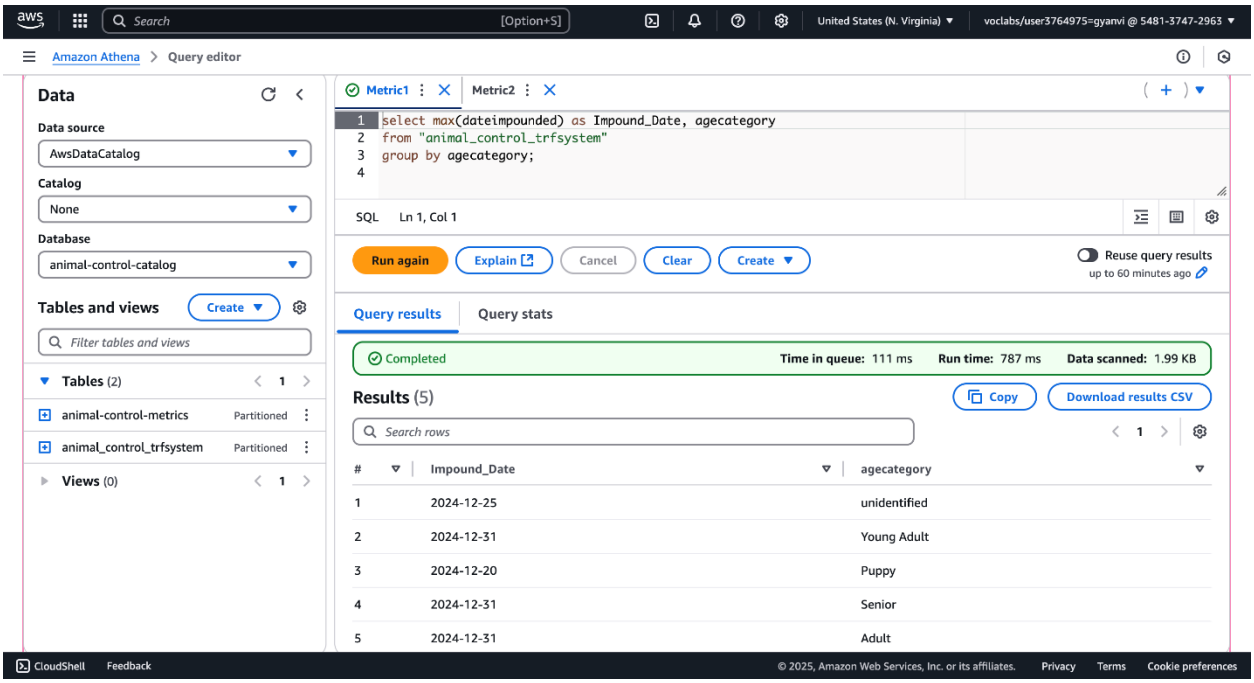


Note. The cleaned dataset is further formatted to drop unnecessary columns. (Source: AWS Glue, *self-work*)

AWS Athena query editor takes our Data catalog as the data source and answers the two business questions. For our analysis, we need only 3 columns- date impounded, breed and age category.

The SQL query for business question 1 selects the maximum date of impoundment and creates an alias as ‘Impound_Date’ and groups it by the age category. The result gives the recent impound date for each animal age category.

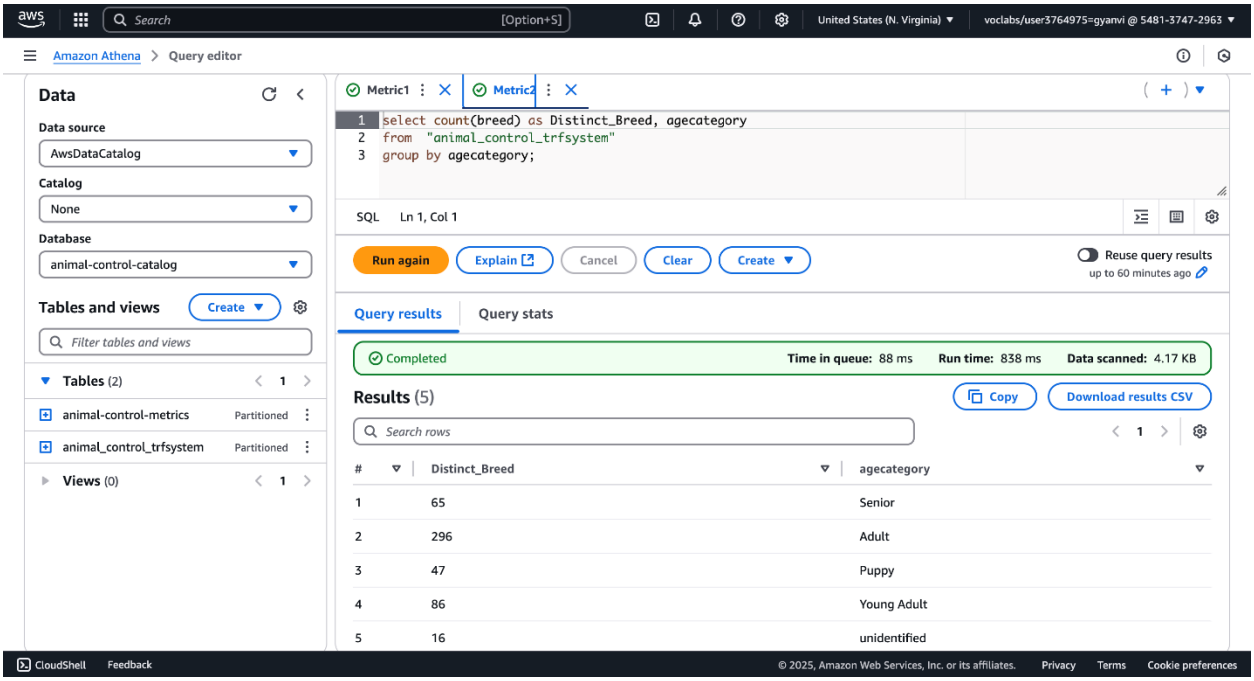
Figure 3: AWS Athena Business Question 1 SQL query



Note. AWS Athena SQL query for business question 1. (Source: AWS Athena, *self-work*)

The SQL query for business question 2 selects the number of breeds and creates an alias as ‘Distinct_Breed’ and groups it by the age category. The result gives the number of distinct breeds for each animal age category.

Figure 4: AWS Athena Business Question 2 SQL query

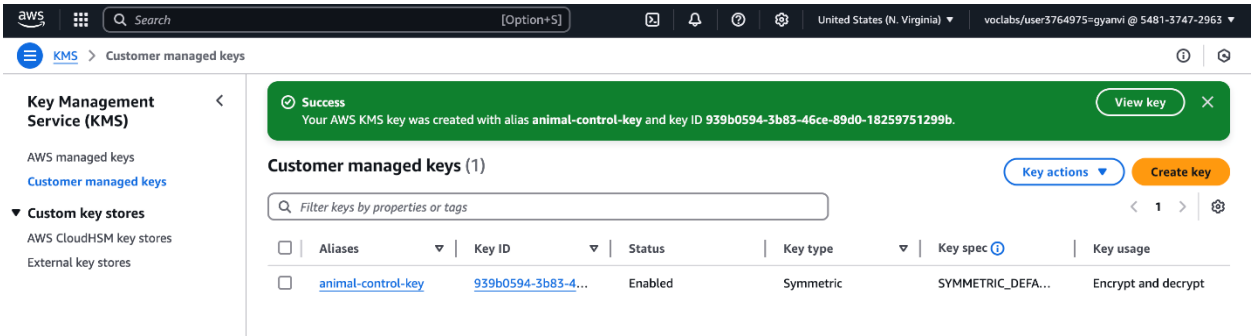


Note. AWS Athena SQL query for business question 2. (Source: AWS Athena, *self-work*)

Step 6: Data Security

Data security deals with creating and managing keys while controlling encryption activities to protect our data. Amazon Key Management System has been used to create a key called ‘animal-control-key’. LabRole is the key administrator and the key user. Encryption has been enabled for this key.

Figure 5: Key created for animal control inventory data



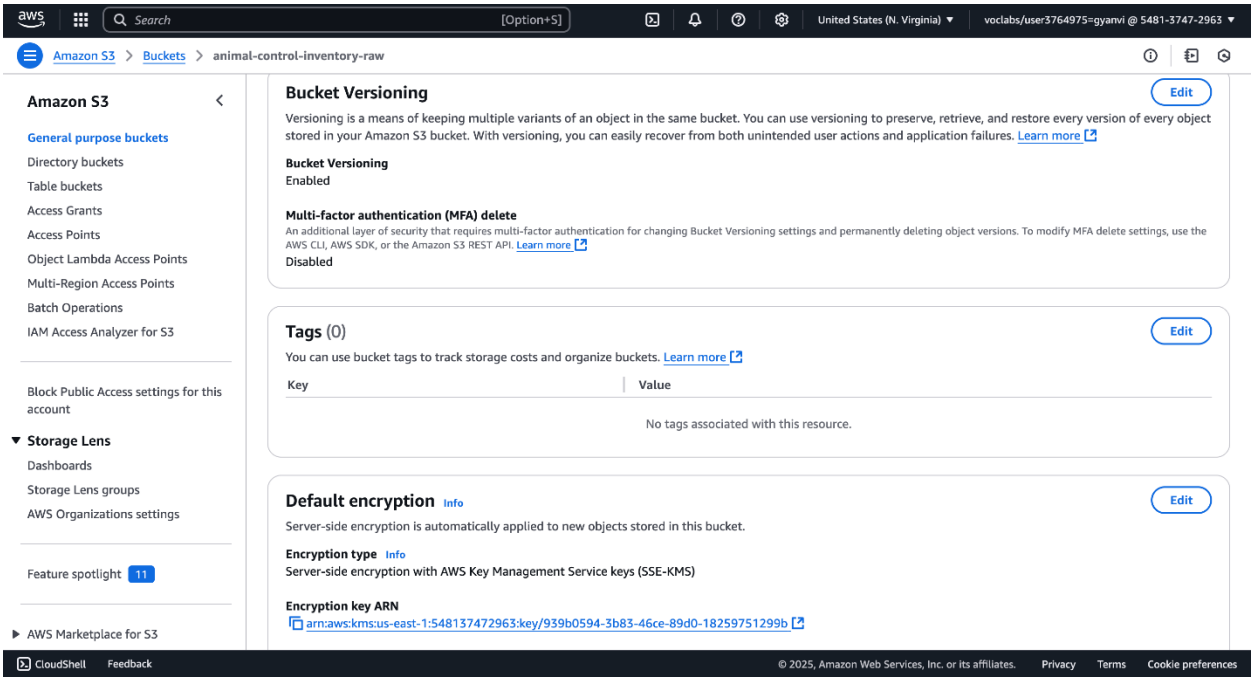
Note. Key created for encryption to be used in animal control inventory dataset. (Source: AWS KMS, *self-work*)

Next, the raw and transformed buckets were managed to provide encryption and replication for enhancing data security. The key ‘animal-control-key’ is used for both the raw and transformed buckets to enable encryption.

For bucket versioning, we have chosen this option to keep our data safe by creating multiple copies of it for any unforeseen event. By creating a new S3 bucket called ‘animal-control-inventory-backup’ for replication rules, the replication rule named ‘animal-control-inventory-replication’ is stored in the new bucket.

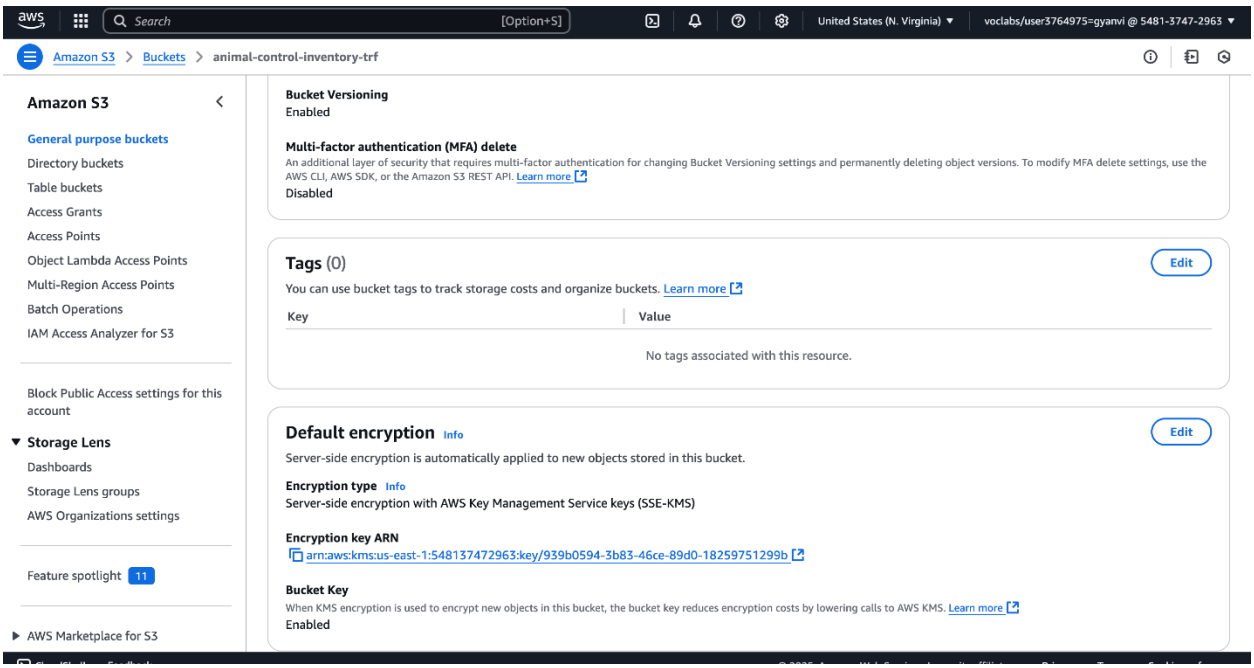
Similarly, for creating the replication rule for the transformed bucket, we have created another S3 bucket called ‘animal-control-trf-backup’. The replication rule called ‘animal-control-trf-replication’ is stored in this new bucket created.

Figure 6: Bucket versioning and encryption for raw bucket



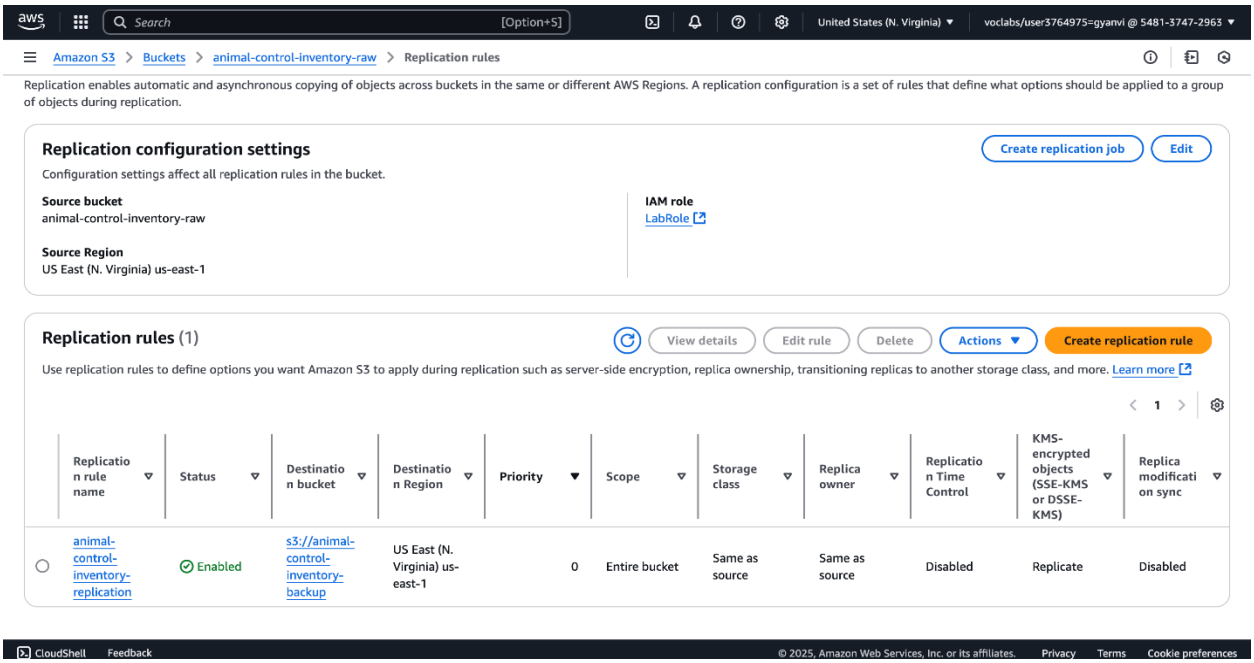
Note. Bucket versioning and encryption for the animal-control-raw bucket. (AWS S3, *self-work).*

Figure 7: Bucket versioning and encryption for transformed bucket



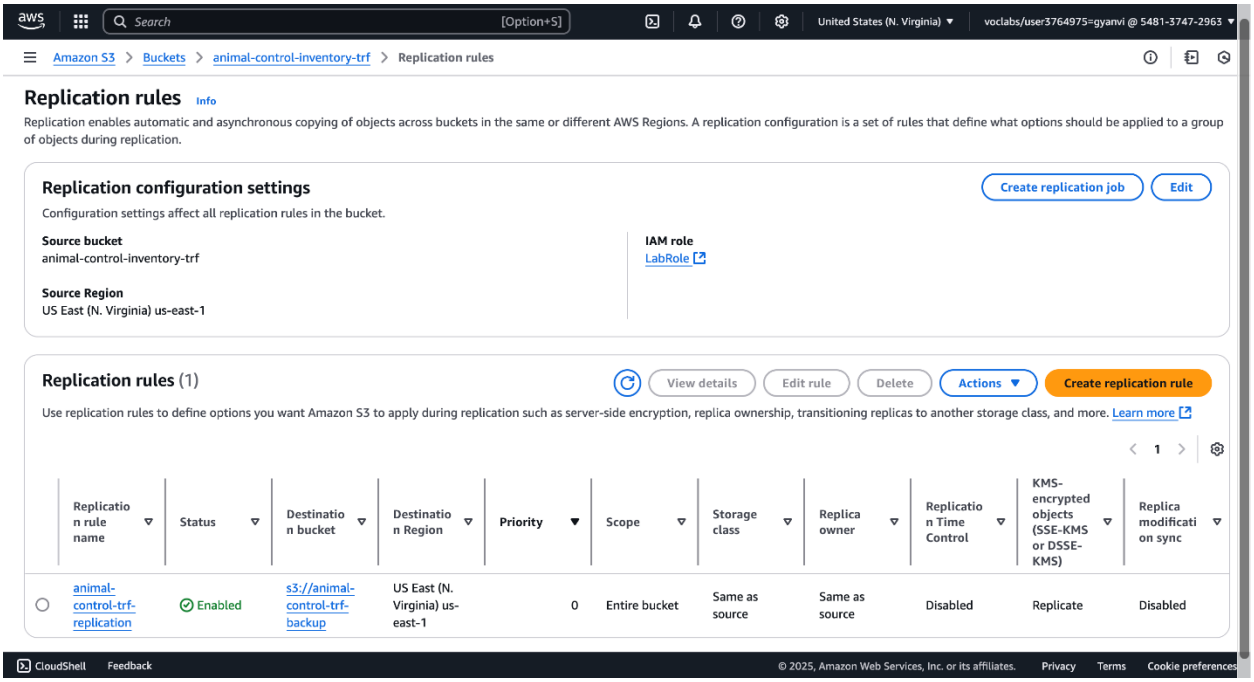
Note. Bucket versioning and encryption for the animal-control-trf bucket. (AWS S3, *self-work).*

Figure 8: Replication rule created for raw bucket



Note. A replication rule was created for the raw zone in the new raw-backup bucket. (AWS S3, *self-work).*

Figure 9: Replication rule created for transformed bucket



Note. A replication rule was created for the transformed zone in the new trf-backup bucket. (AWS S3, *self-work).*

Step 7: Data Governance

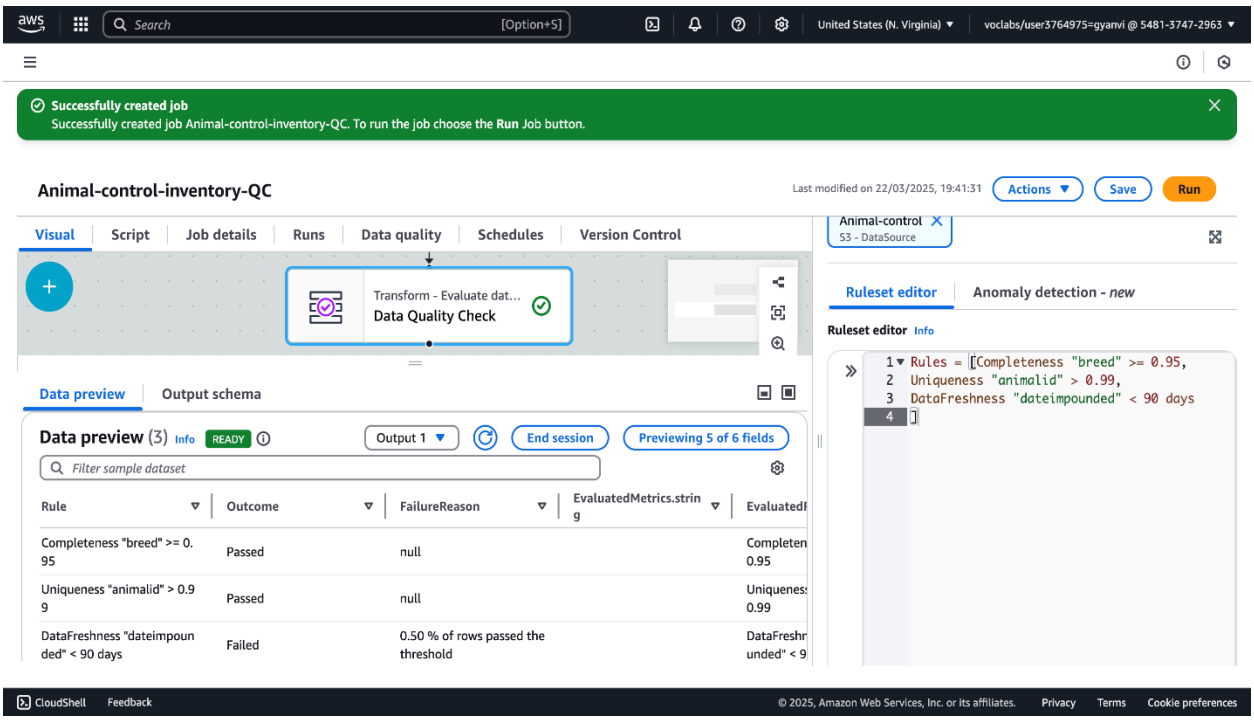
The data governance step was carried out in AWS Glue where the visual ETL pipeline was created. This pipeline involves checking data for its quality using three parameters namely, completeness, uniqueness and freshness. The pipeline is named ‘Animal-control-inventory-QC’ and takes the data from the animal-control-inventory raw bucket. Next, the ruleset editor creates the following three rules:

1. Completeness of the *‘breed’* column should be greater than or equal to 0.95

2. Uniqueness concerns the primary key column called *'animalid'* which should be greater than 0.99

3. Freshness has a date column called *'dateimpounded'* less than 90 days

Figure 10: Rules created for animal-control-inventory-QC



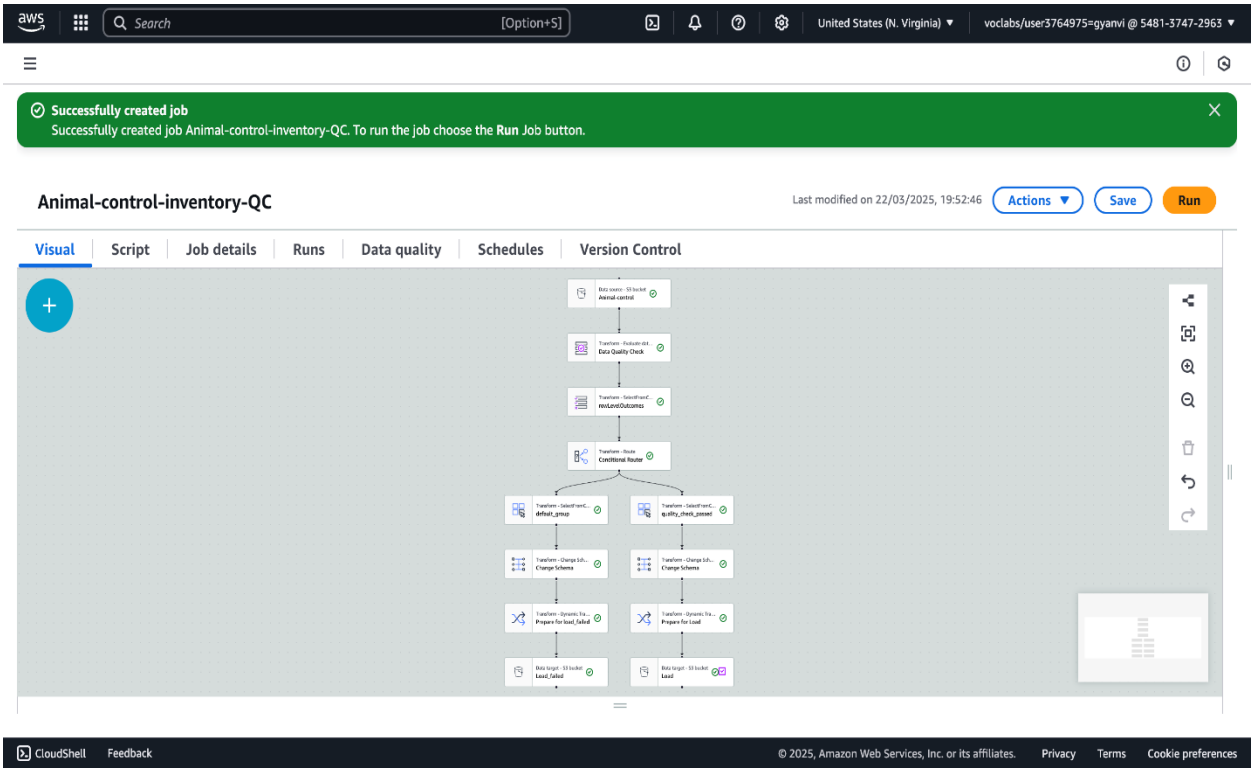
Note. Evaluate data quality under the transform section in the ETL pipeline. (AWS Glue, *self-work).*

Two of the rules have passed and one has failed based on the conditions provided under the ruleset editor. Now, the following steps have used transform features like transform-route for creating two groups called, '*quality_check_passed'* and the other is the default group.

The logical operator is AND and the key is the Data quality evaluation result. The operation is 'matches' as "Passed" is the string value. By employing the usual steps of dropping

unnecessary columns of data quality check under the Change Schema feature and then using auto-balancing for a single output, we perform the steps for both passed and failed sets.

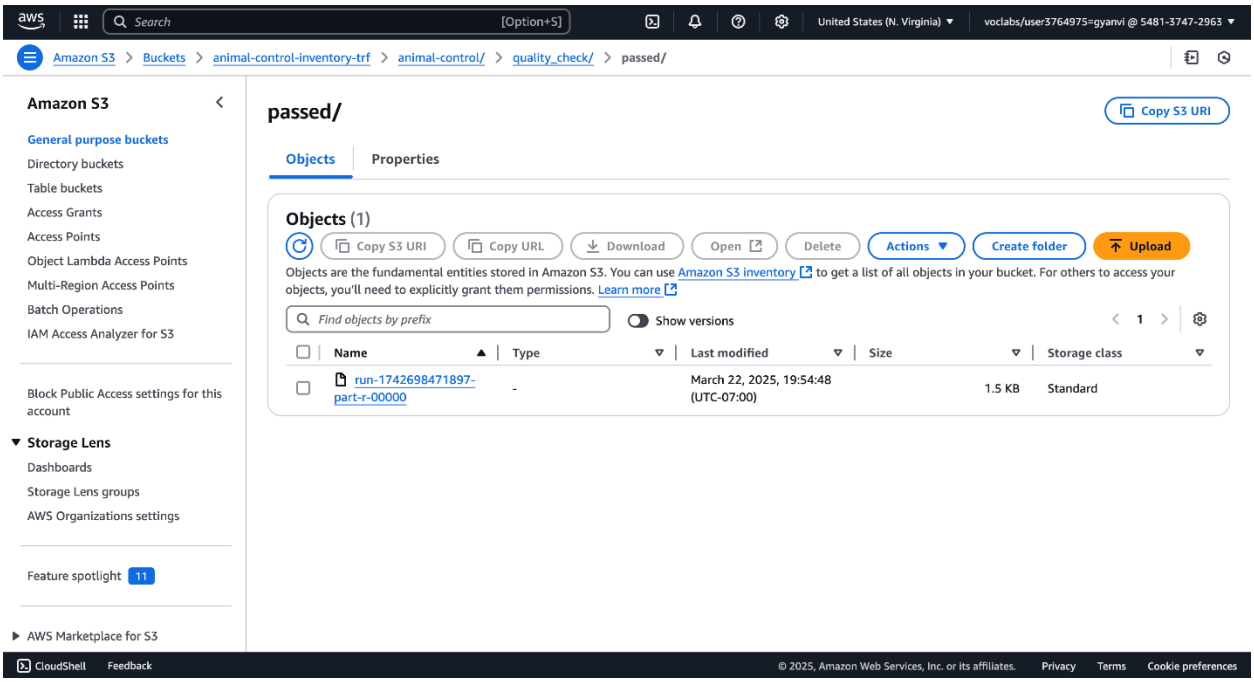
Figure 11: ETL pipeline for animal control inventory quality check



Note. The entire ETL pipeline was created for the data governance step for quality check of animal control inventory. (AWS Glue, *self-work).*

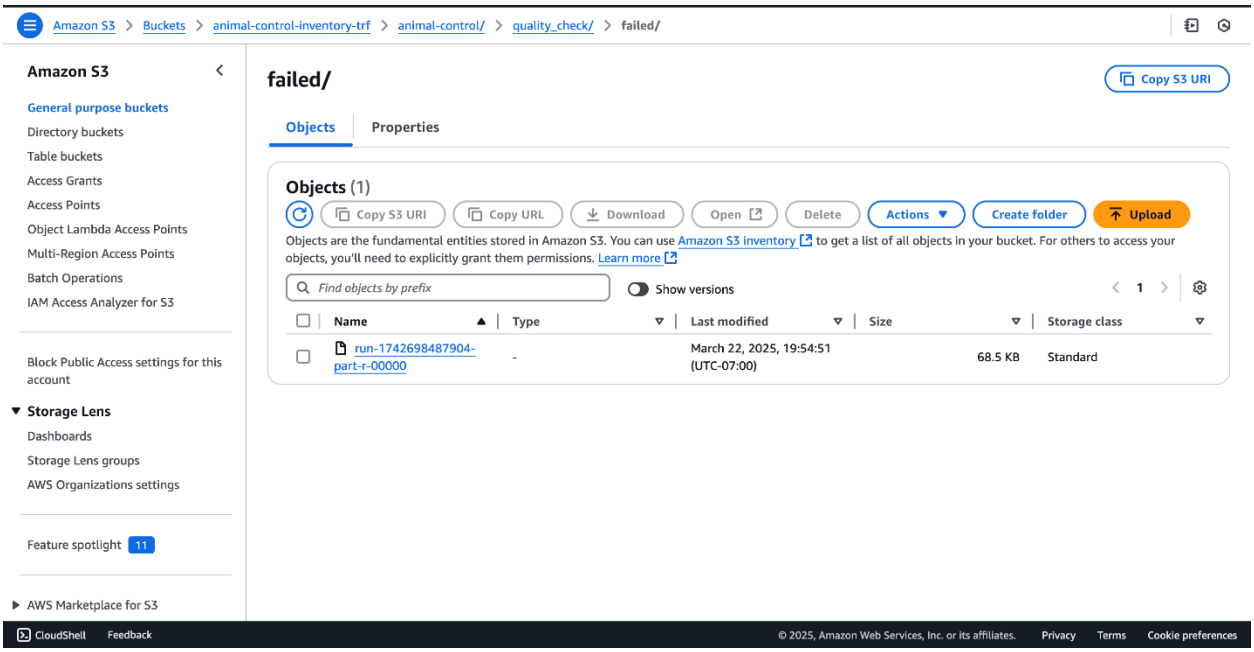
In the transformed bucket, we created a folder called ‘Quality_check’ which has two sub-folders called ‘Passed’ and ‘Failed’. The single CSV output for passed goes into the passed folder and the same goes for the failed folder.

Figure 12: Job output for ‘Passed’ folder



Note. AWS S3 transformed bucket containing the output of the passed data quality check (AWS S3, *self-work).*

Figure 13: Job output for the 'Failed' folder

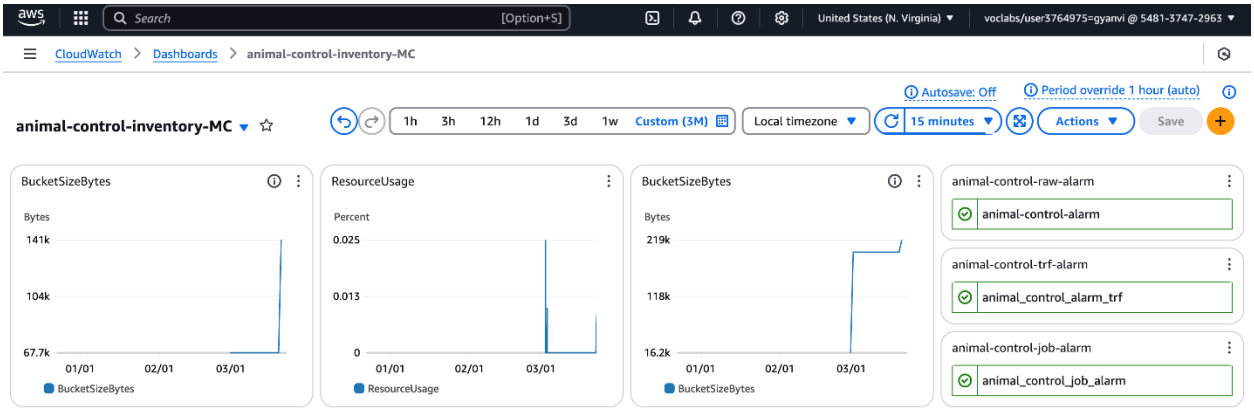


Note. AWS S3 transformed bucket containing the output of the failed data quality check (AWS S3, *self-work).*

Step 8: Data Monitoring

For data monitoring, we have used the AWS CloudWatch feature that monitors resource usage which is essential in cost and storage optimization. The dashboard created is named 'animal-control-inventory-MC' which contains 3 metrics and 3 alarms for the respective metrics. A simple line widget is used for the three metrics- Raw S3 bucket, Transformed S3 bucket and Glue JobRun. The timeline is customized for 3 months.

Figure 14: Dashboard created on CloudWatch



Note. The overview of the dashboard contains the three metrics and three alarms. (AWS CloudWatch, *self-work).*

Next, the alarms created for the S3 service have an average as the stat and 1 day as the time period. The Glue service has a time period of 5 minutes.

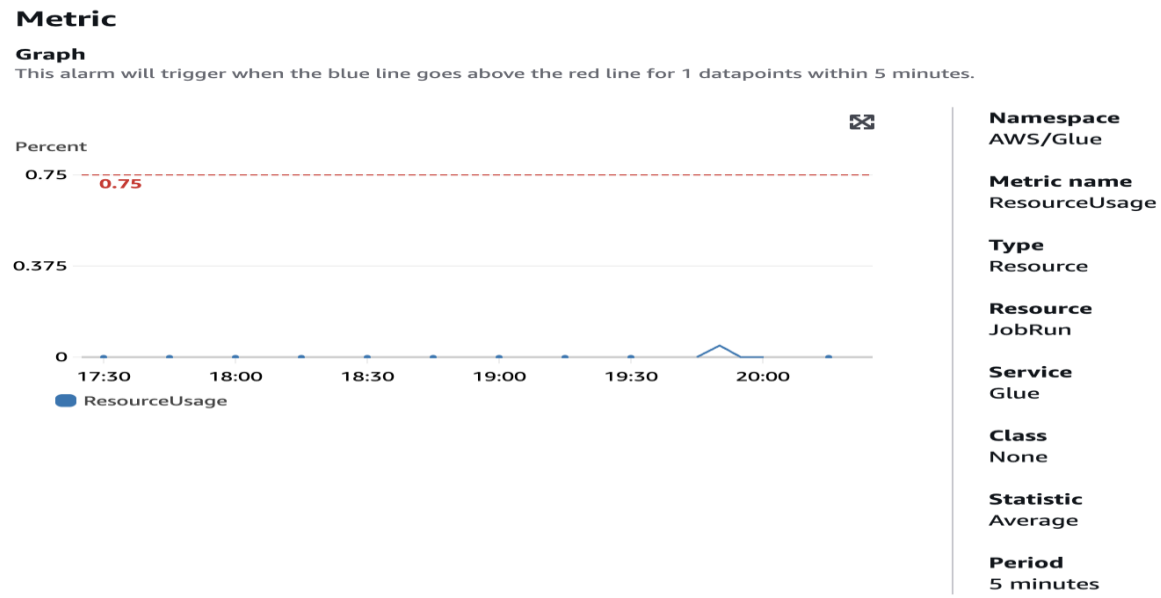
The threshold is set for the three metrics as:

1. Raw S3 bucket bucket size bytes: 180,000

2. Transformed S3 bucket size bytes: 300,000

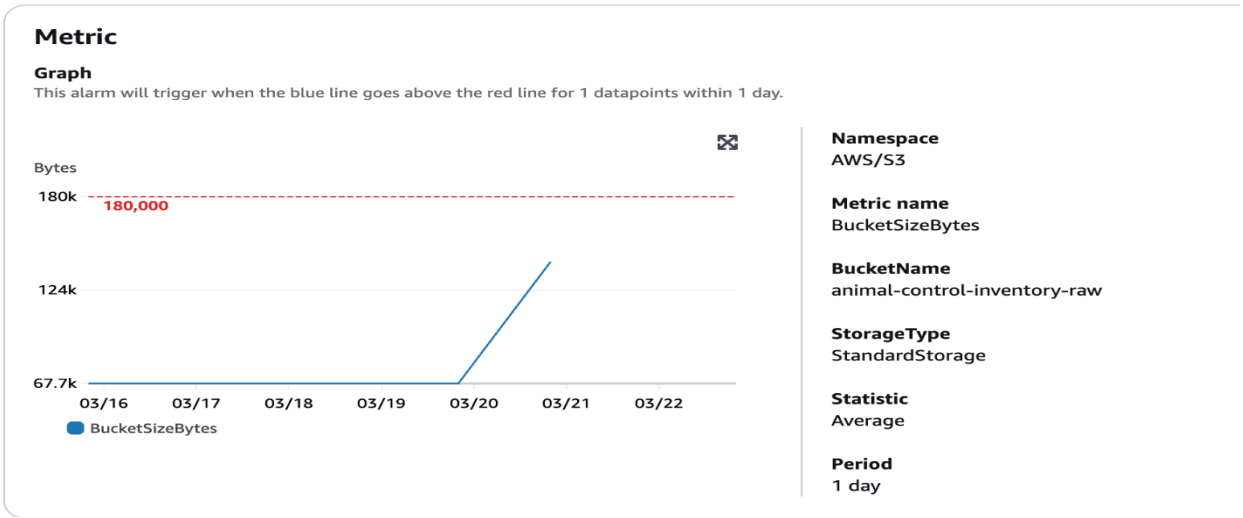
3. JobRun percent: 0.75

Figure 15: AWS Glue alarm



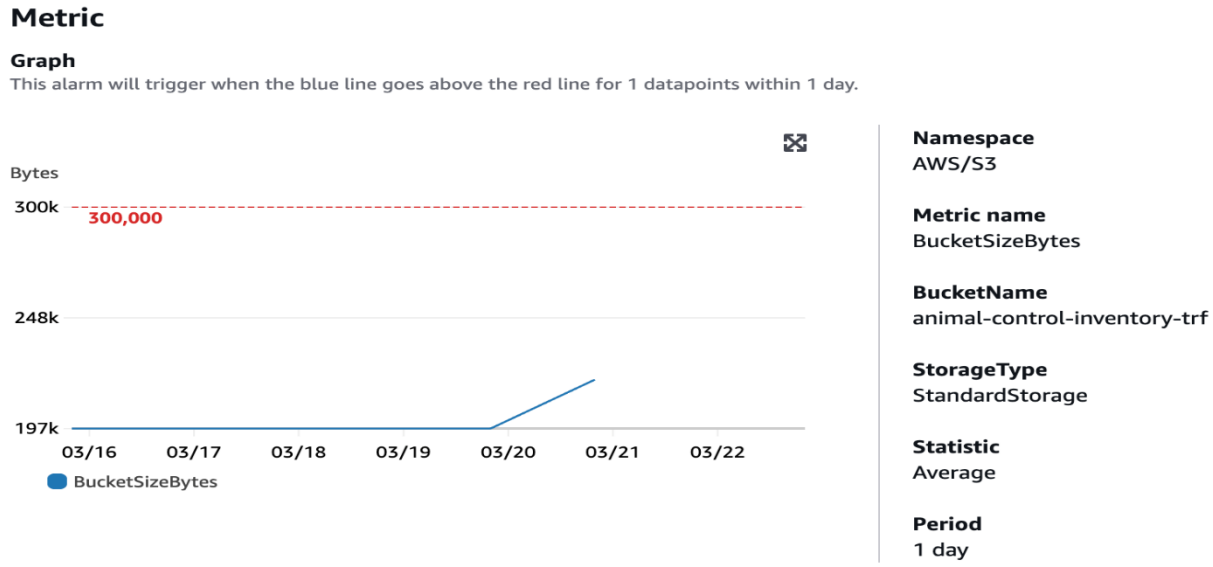
Note. Overview of the AWS Glue alarm with 0.75 percent as threshold. (AWS CloudWatch, *self-work).*

Figure 16: AWS S3 Raw bucket alarm



Note. Overview of the AWS S3 Raw bucket alarm with 180,000 bytes as threshold (AWS CloudWatch, *self-work).*

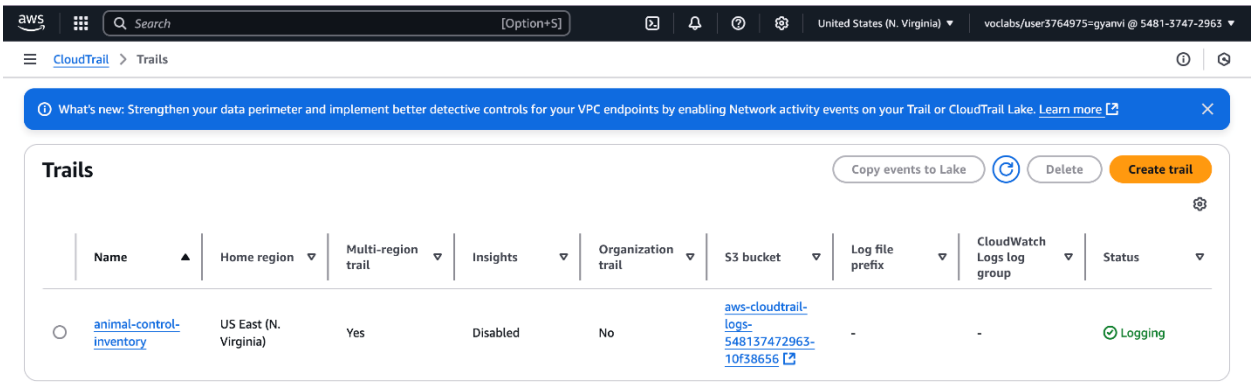
Figure 17: AWS S3 transformed bucket alarm



Note. Overview of the AWS S3 Transformed bucket alarm with 300,000 bytes as threshold (AWS CloudWatch, *self-work).*

We can use AWS Cloudtrail to monitor user activity and understand patterns of usage. For this, we have created a trail called ‘animal-control-inventory’ which contains all steps taken during the session.

Figure 18: AWS CloudTrail used to create a trail

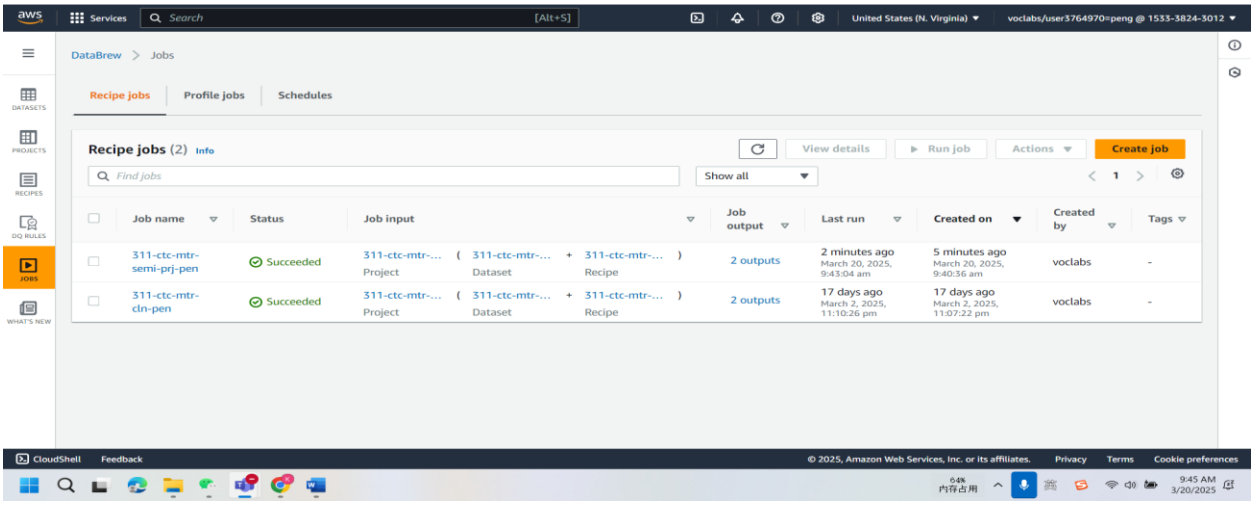


Note. Trail created in AWS CloudTrail to understand user activity and usage patterns for cost and resource optimization (AWS CloudTrail, *self-work).*

DAP Implementation (Individual work – Peng Wang)

Step 5: Data Analysis

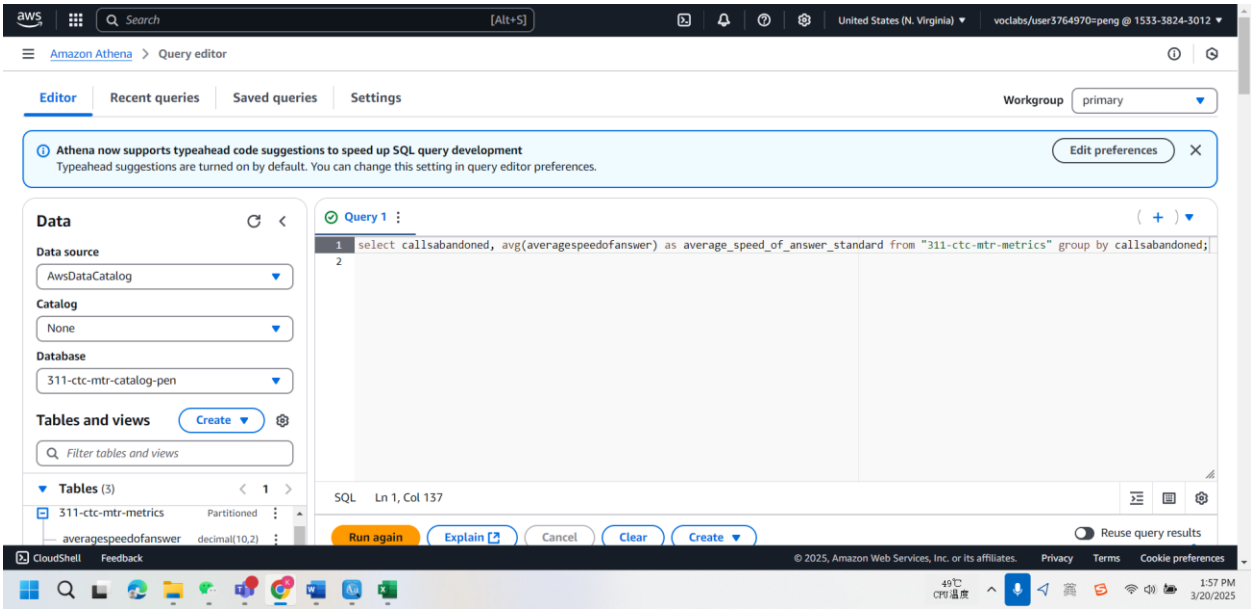
Figure 19: Semi-dataset jobs



Note. The screenshot shows the semi-dataset jobs. Source from AWS.

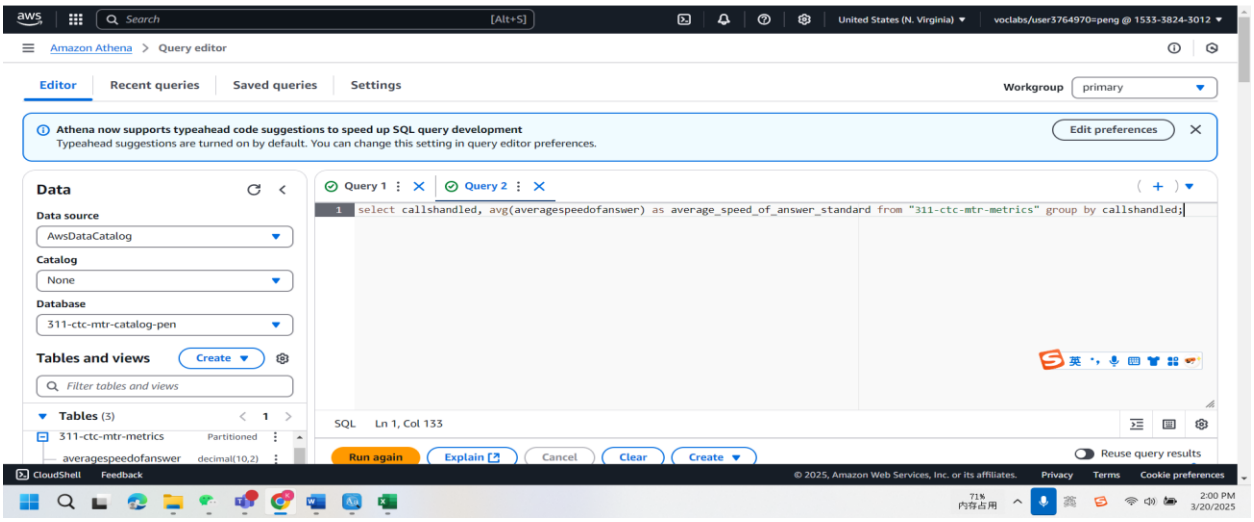
Explanation: I created the semi-dataset, but I found I have already created the cleaned dataset, which can be used for data analysis, so I think it is not necessary to create the semi-dataset.

Figure 20: SQL Syntax in Athena



Note. The screenshot shows the first SQL syntax in Athena. Source from AWS.

Figure 21: SQL Syntax in Athena



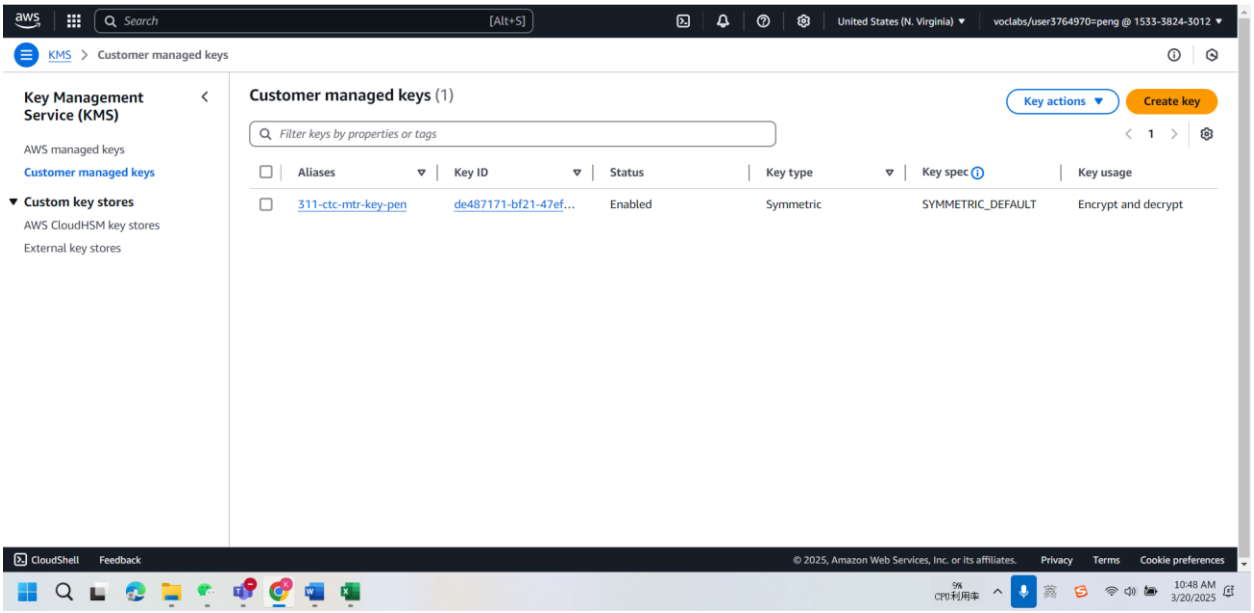
Note. The screenshot shows the second SQL syntax in Athena. Source from AWS.

Explanation: I analyzed through SQL syntax in Athena. That is because Athena provides the functions to proceed with business questions by SQL syntax. There are two questions that need

to be analyzed. The first one is the calls abandoned analysis, compared with an average speed of answer. The second one is the calls handled analysis, compared with an average speed of answer. Specifically, I set the standard value as the average of average speed of the answer. In this case, calls abandoned data and calls handled data can be shown whether it is more than this standard value or less than the standard value.

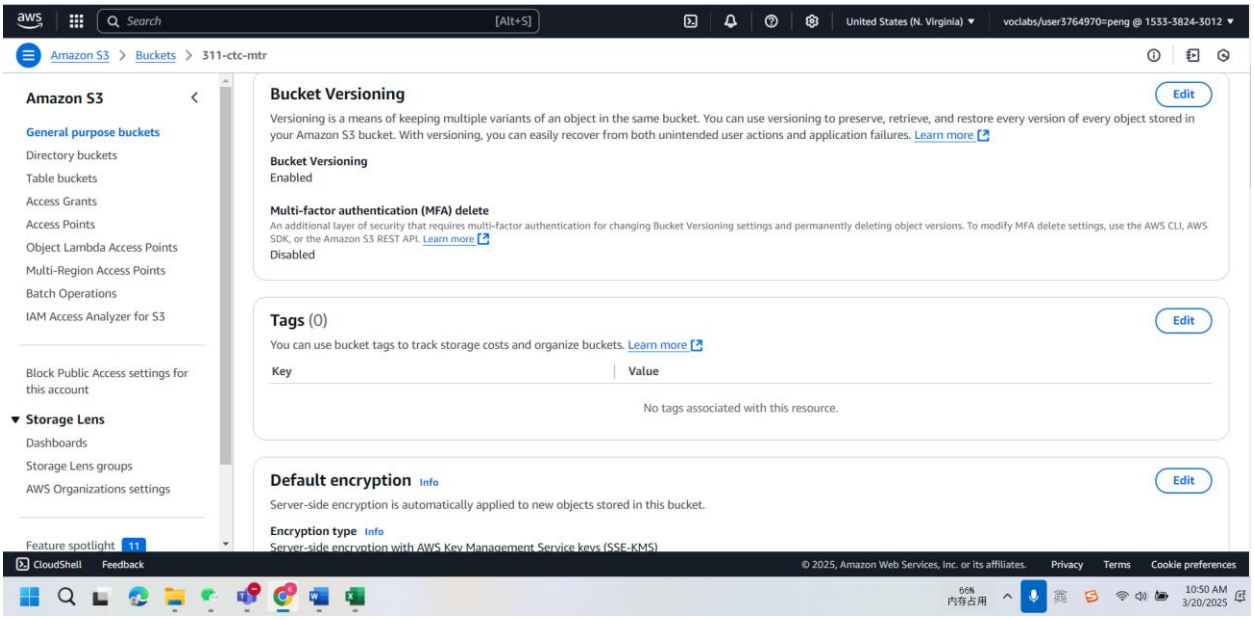
Step 6: Data Security

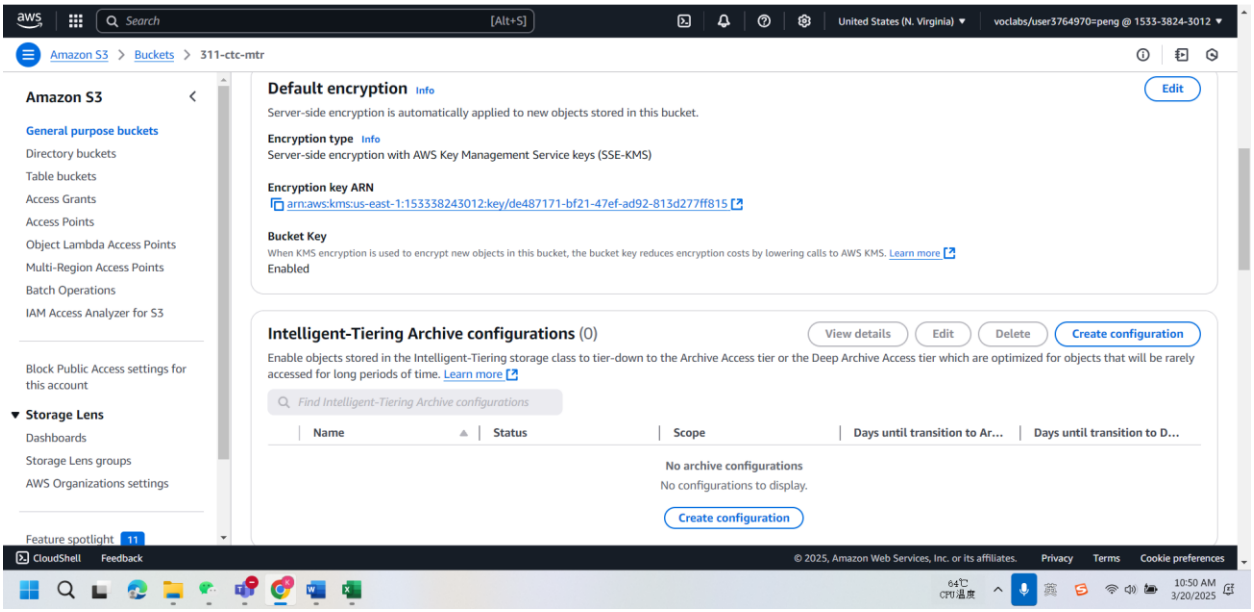
Figure 22: Key Management Service



Note. The screenshot shows the key management service. Source from AWS.

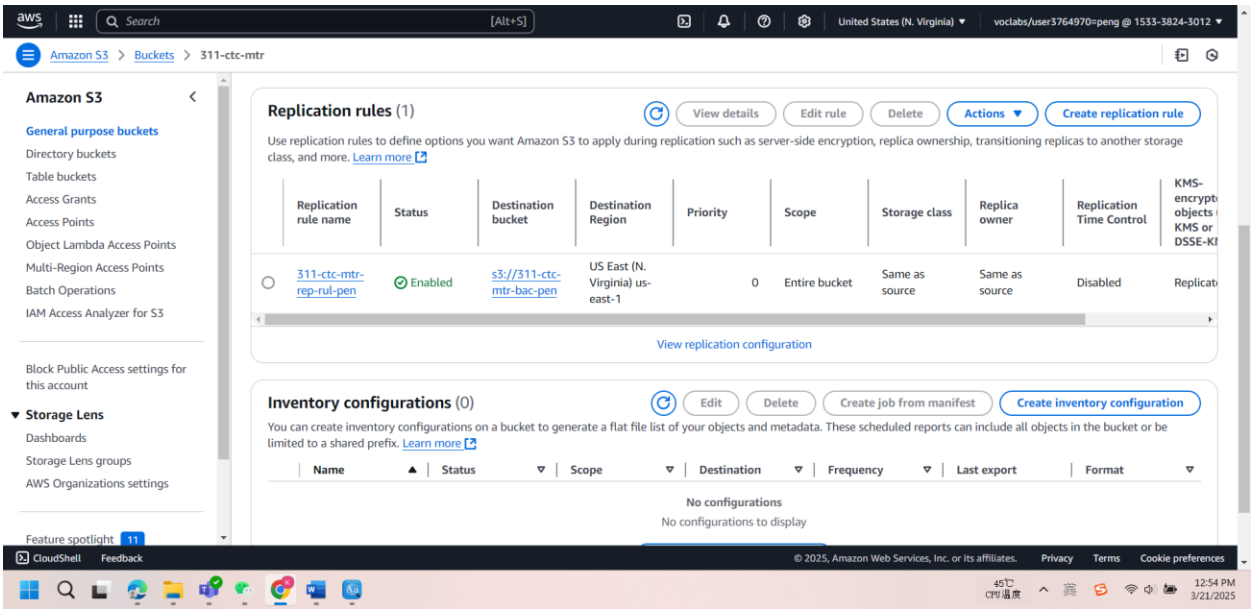
Figure 23: Raw Bucket Versioning and Default Encryption





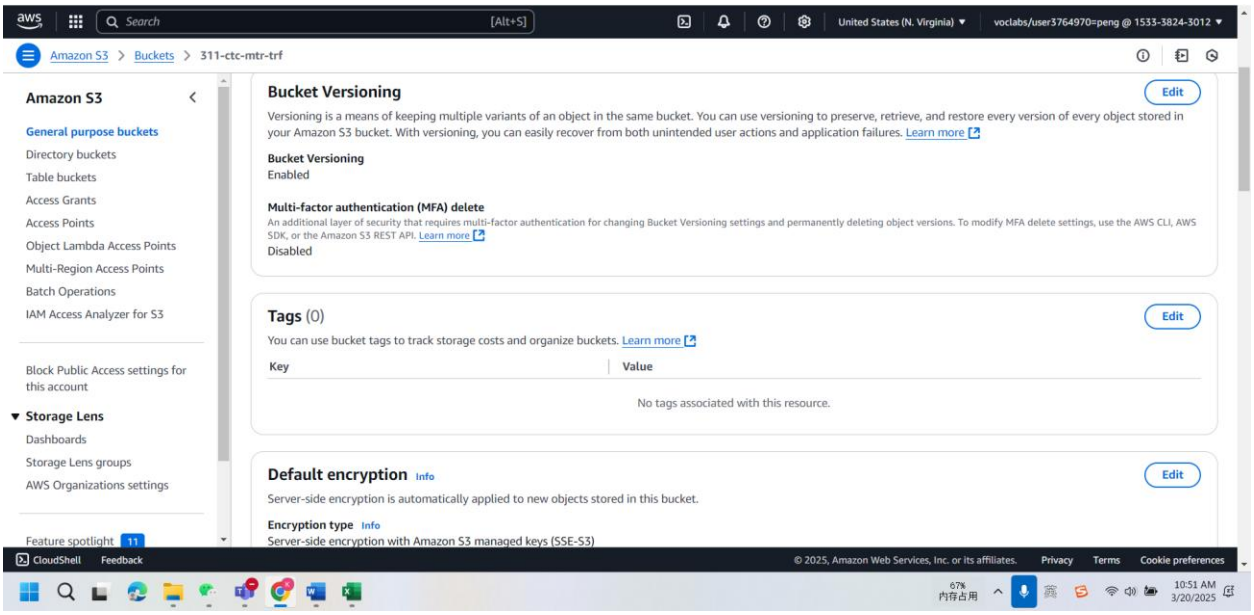
Note. The screenshot shows the raw bucket versioning and default encryption. Source from AWS.

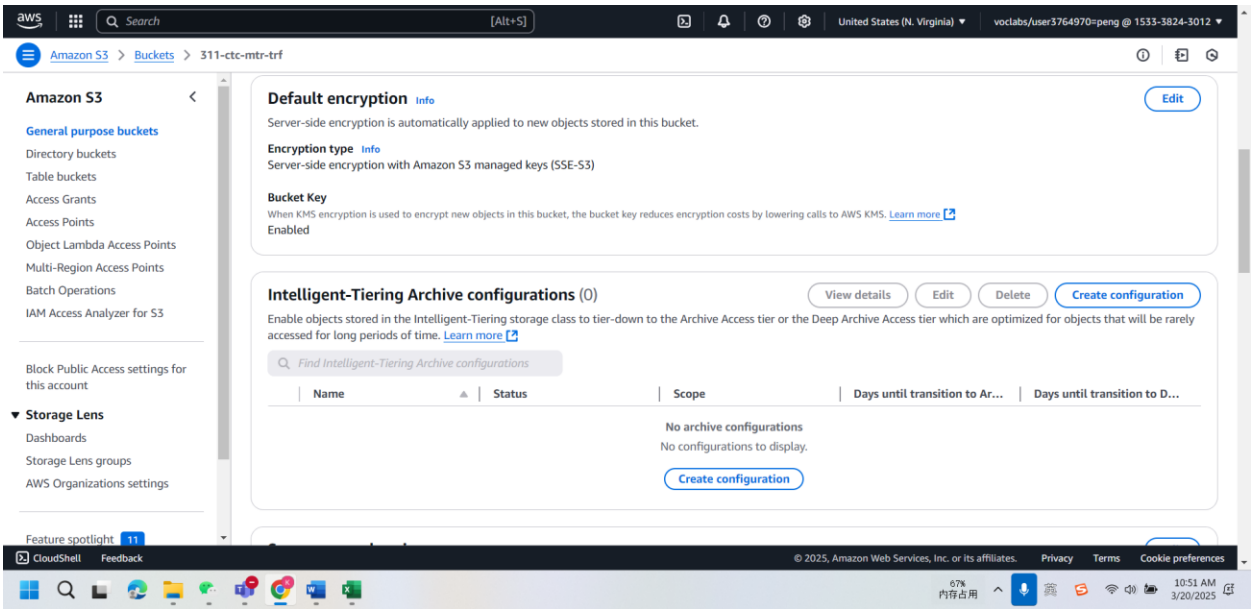
Figure 24: Replication Rules in Raw Bucket



Note. The screenshot shows the replication rules in the raw bucket. Source from AWS.

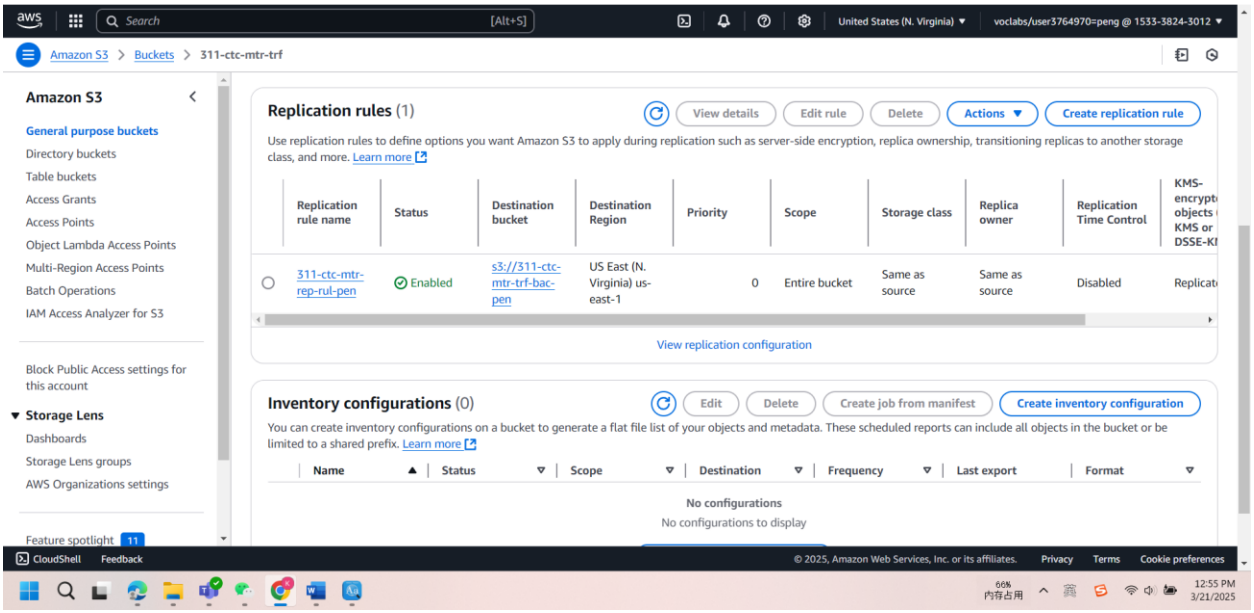
Figure 25: Transfer Bucket Versioning and Default Encryption





Note. The screenshot shows the transfer bucket versioning and default encryption. Source from AWS.

Figure 26: Replication Rules in Transfer Bucket

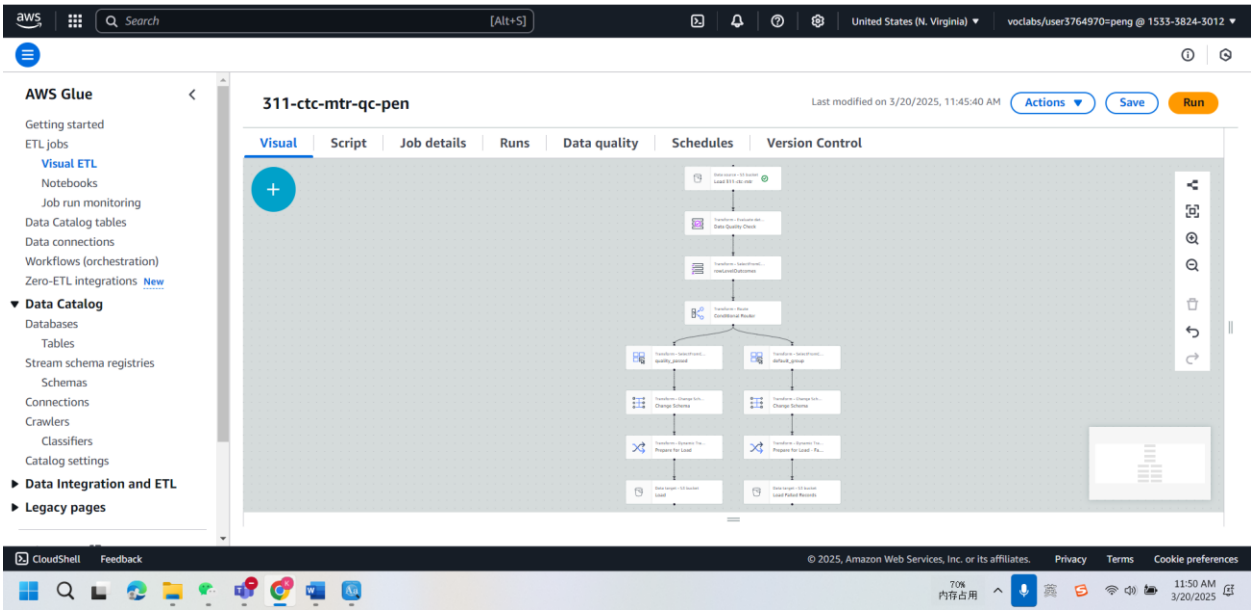


Note. The screenshot shows the replication rules in the transfer bucket. Source from AWS.

Explanation: I set the key through KMS, and then, I set the bucket versioning and default encryption. Finally, it is necessary to set the replication rules in the raw bucket and transfer bucket. The reason why I set the key in KMS is that KMS kyes can reduce the risk and encrypt the sensitive data, the bucket versioning is mainly to prevent data loss, and the default encryption is mainly to avoid unauthorized access to stored data. Overall, this operation can ensure data security.

Step 7: Data Governance

Figure 27: Quality Check in Visual ETL

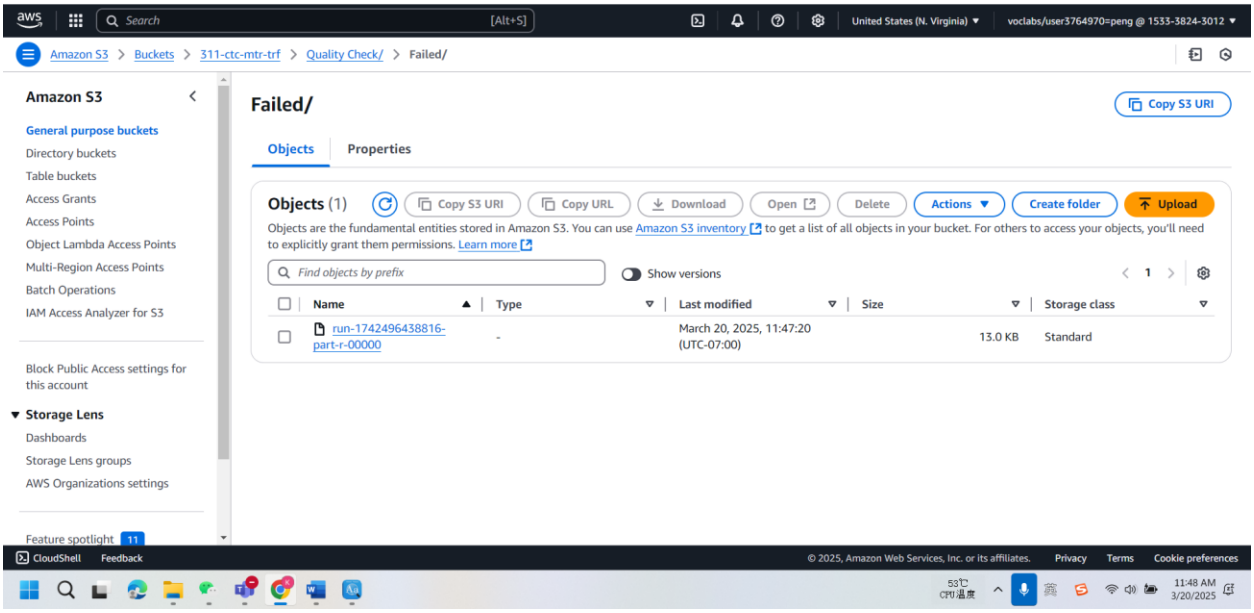


Note. The screenshot shows the visual ETL for quality check. Source from AWS.

Explanation: I did the ruleset for data quality and then set the conditional router, including passed and failed, and then changed the schema before load, including dropping the useless columns. Finally, I loaded the Passed and Failed into the corresponding folders. This part mainly focuses on passed data and failed data based on specific rules.

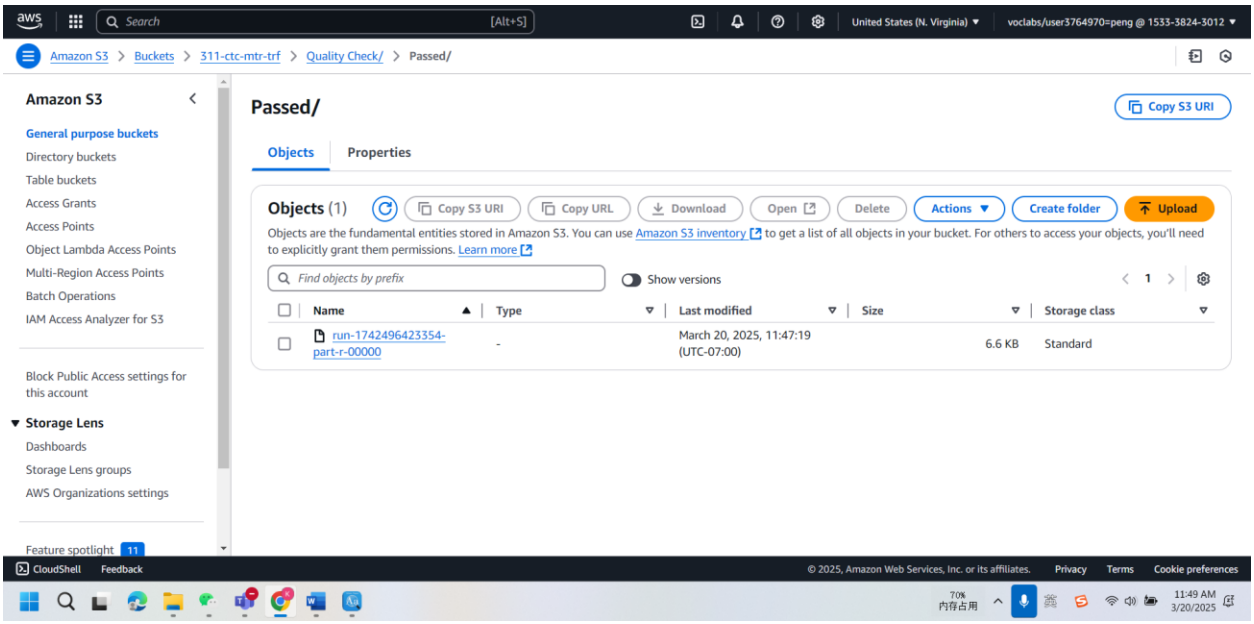
The whole operation is mainly to organize the data better. For example, the data in the Passed subfolder is cleaned and validated, which can be processed successfully. However, the data in the Failed subfolder is incorrect and incomplete, which cannot be processed better. In this case, better data quality control can be achieved. Moreover, visual ETL is beneficial in reducing errors and speeding up data transformation.

Figure 28: Failed Dataset in Transfer Bucket



Note. The screenshot shows the failed dataset in the transfer bucket. Source from AWS.

Figure 29: Passed Dataset in Transfer Bucket

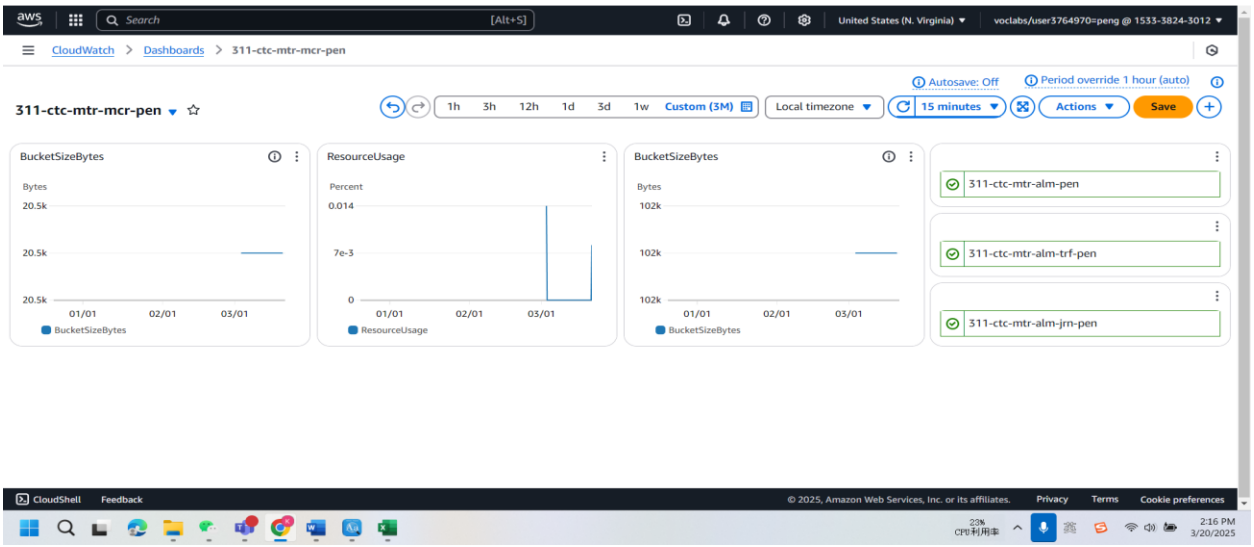


Note. The screenshot shows the passed dataset in the transfer bucket. Source from AWS.

Explanation: After loading the passed and failed in Visual ETL, the corresponding datasets have already been published into each sub-bucket in the transfer bucket, which can be downloaded for different uses.

Step 8: Data Monitoring

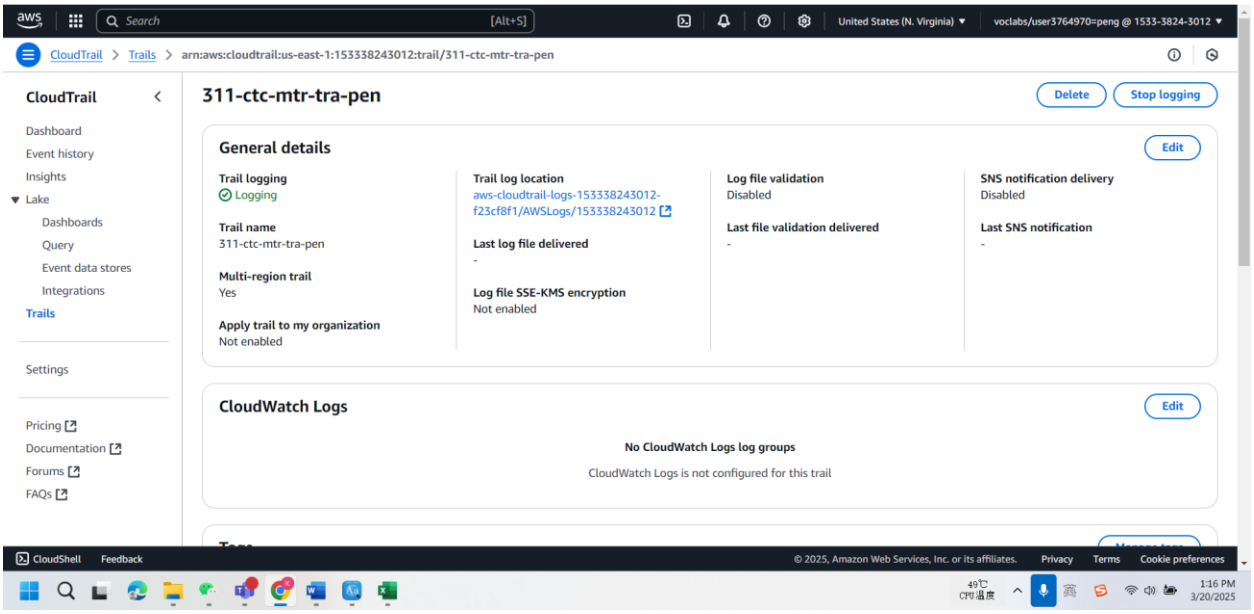
Figure 30: Dashboard and Alarms in CloudWatch



Note. The screenshot shows the dashboard and alarms in CloudWatch. Source from AWS.

Explanation: I established the dashboard in CloudWatch, including the raw bucket and the transfer bucket in S3, and the JobRun in Glue. Finally, I also established three alarms for the raw bucket, transfer bucket, and the jobrun, which were added to the dashboard. Regarding the alarms, it is necessary to set the threshold for each alarm, and the threshold is based on the dataset. For example, I set the threshold as 40000 for the bucket size bytes and 1 day to monitor the data. That is because this threshold is suitable for this bucket, which is originally upper. The period of 1-day monitoring data is mainly to reduce the cost. Finally, the dashboard can visualize the comprehensive view of key metrics, which can achieve the goal of monitoring the data, and alarms are mainly related to thresholds, which can monitor the issue before impacting users.

Figure 31: Trail in CloudTrail



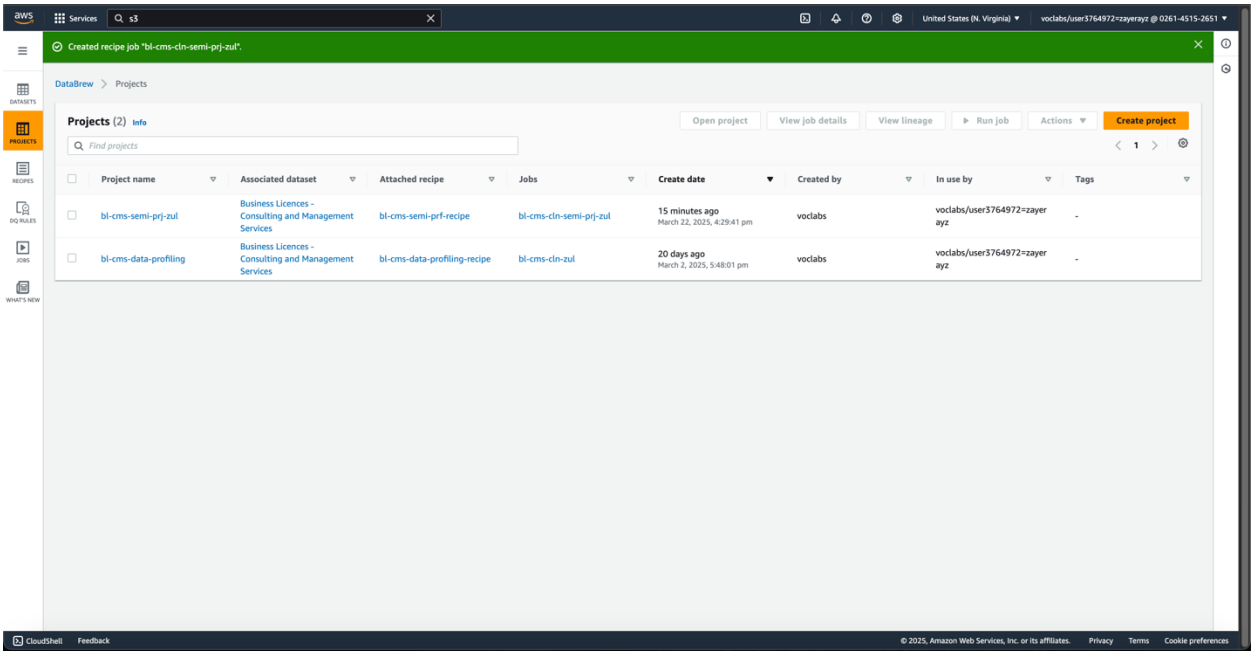
Note. The screenshot shows the trail in CloudTrail. Source from AWS.

Explanation: I established the trail in CloudTrail. That is because I think this operation is essential to do the data monitoring by detecting threats and unauthorized access.

DAP Implementation (Individual work - Muhammad Zulqarnain Shahzad)

Step 5: Data Analysis

Figure 32: Data Brew Projects – Semi Dataset Setup



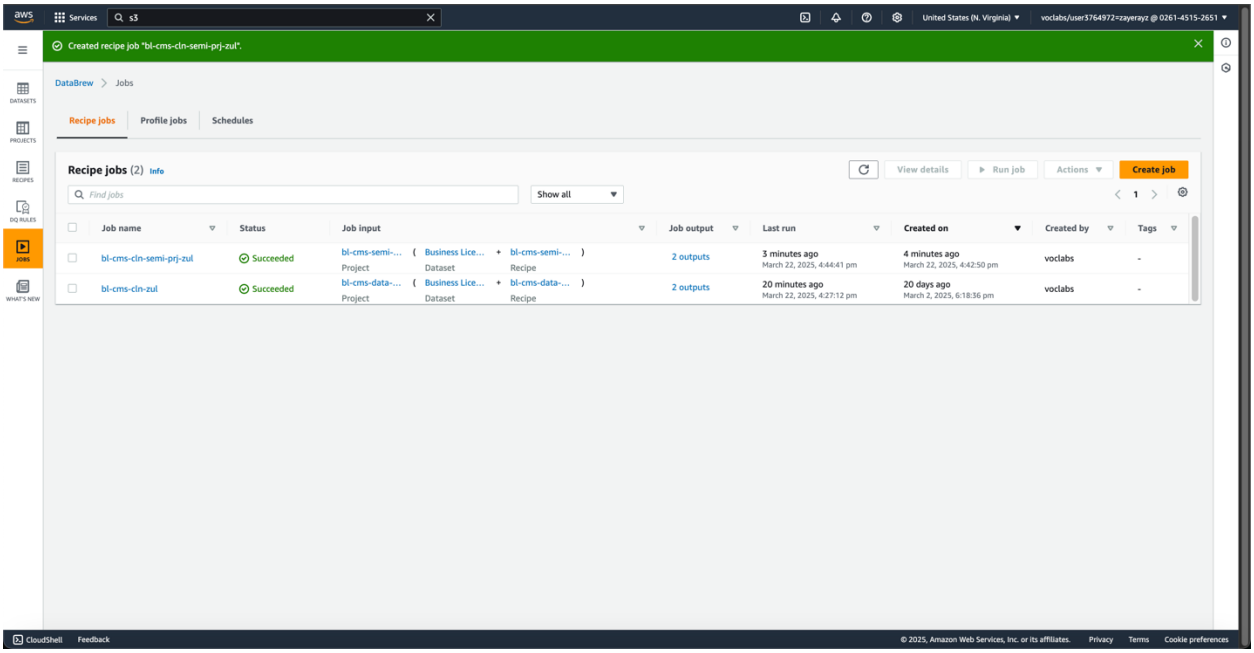
Note. This screenshot shows that I created a new Glue DataBrew project named bl-cms-semi-prj-zul to work on my semi dataset based on the raw version of Business Licences – Consulting and Management Services. Source: AWS Glue DataBrew, *self-work*

Explanation

I just copy my old project from part 1 and made new one for part 2 to show I can handle semi dataset too. It's same data but just to make it look structured like everyone. Professor said

we don’t need new data, but structure is important. So, I use same dataset but made new project with new name.

Figure 33: Data Brew Recipe Jobs – Semi Cleaning Job Execution

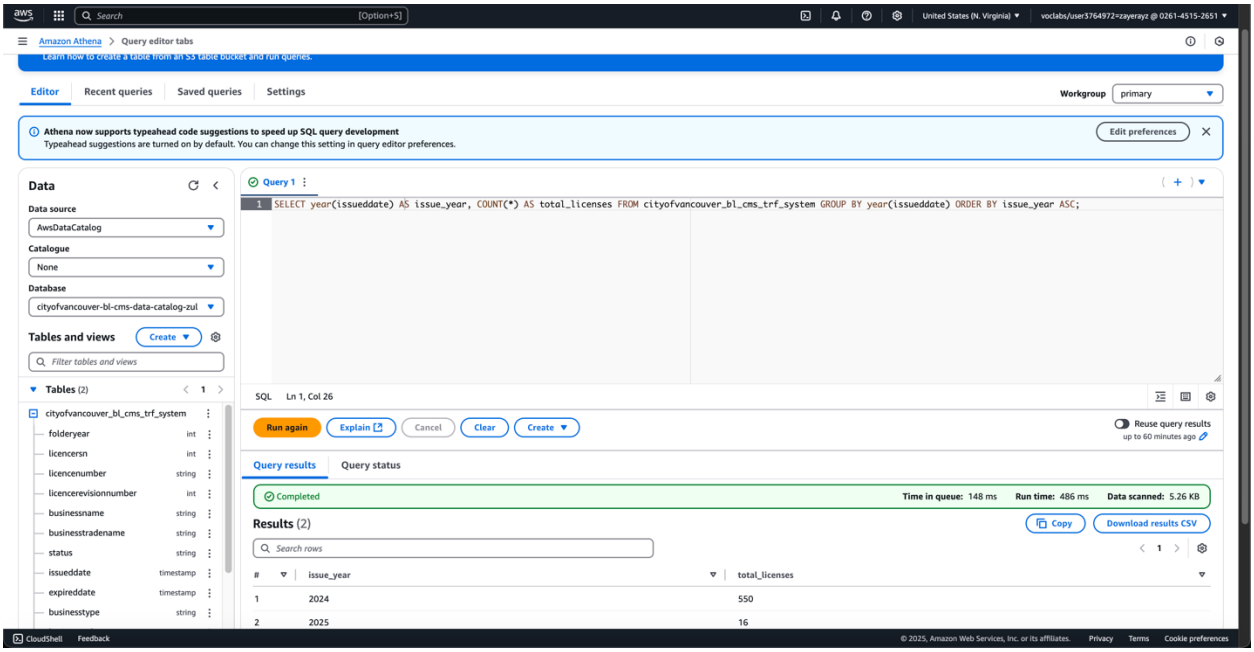


Note. This screenshot shows the job bl-cms-cln-semi-prj-zul was created and successfully ran to process the semi dataset and store the output in S3 semi/user and semi/system. Source: AWS Glue DataBrew, *self-work*

Explanation

This is the job I made from the semi project to do a basic run on the dataset. I didn’t need to do much cleaning again because it was already clean from before. But I still ran the job just to complete the step and make sure I can track how the data flows from raw to semi. It saves the output into the right folders in S3 and shows that I understand how to structure things with different stages like raw, semi, and transform. So, this is more about keeping a clear data process, even if the content didn’t change much.

Figure 34: Business Licenses Issued by Year – Athena SQL Query

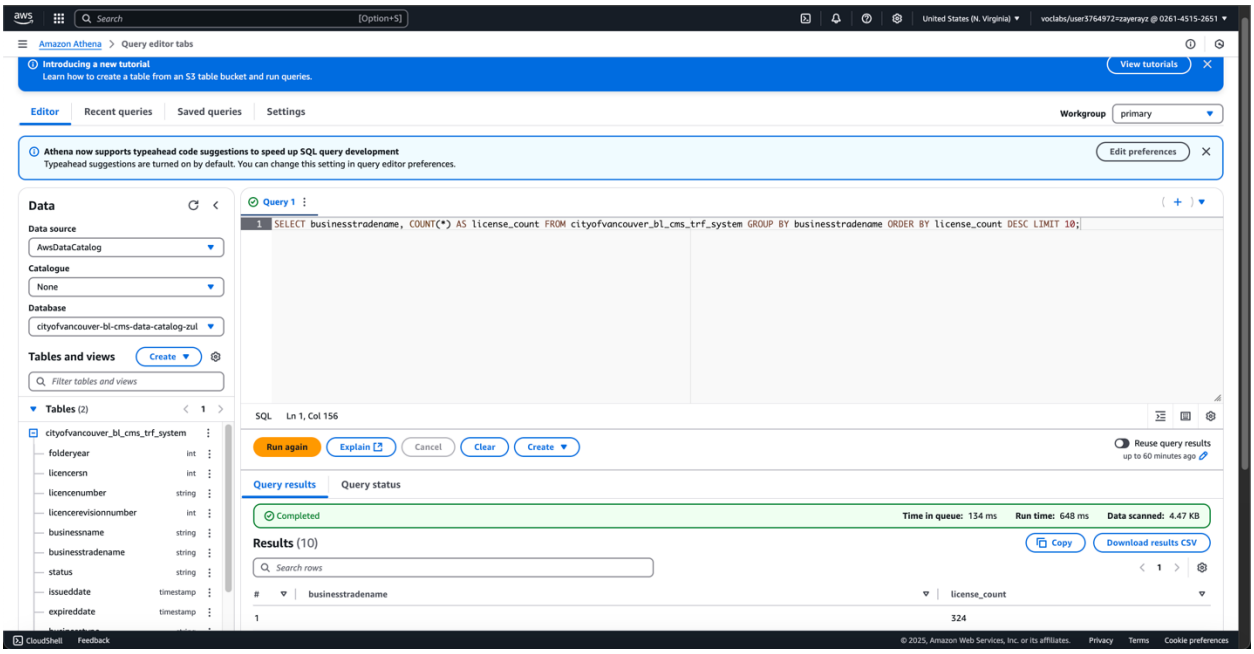


Note. This query shows the number of consulting licenses issued each year using the issued date field. The result shows 550 licenses in 2024. Source: Self-work, AWS Athena Query Editor

Explanation

I wanted to see like how many licenses are given each year, so I ran this query. It's just counting how many new consulting businesses got licenses by year. 2024 is big, 2025 is just started. This helps to see the trend and business activity, if it's going up or down.

Figure 35: Top 10 Business Trade Names by License Count – Athena SQL Query

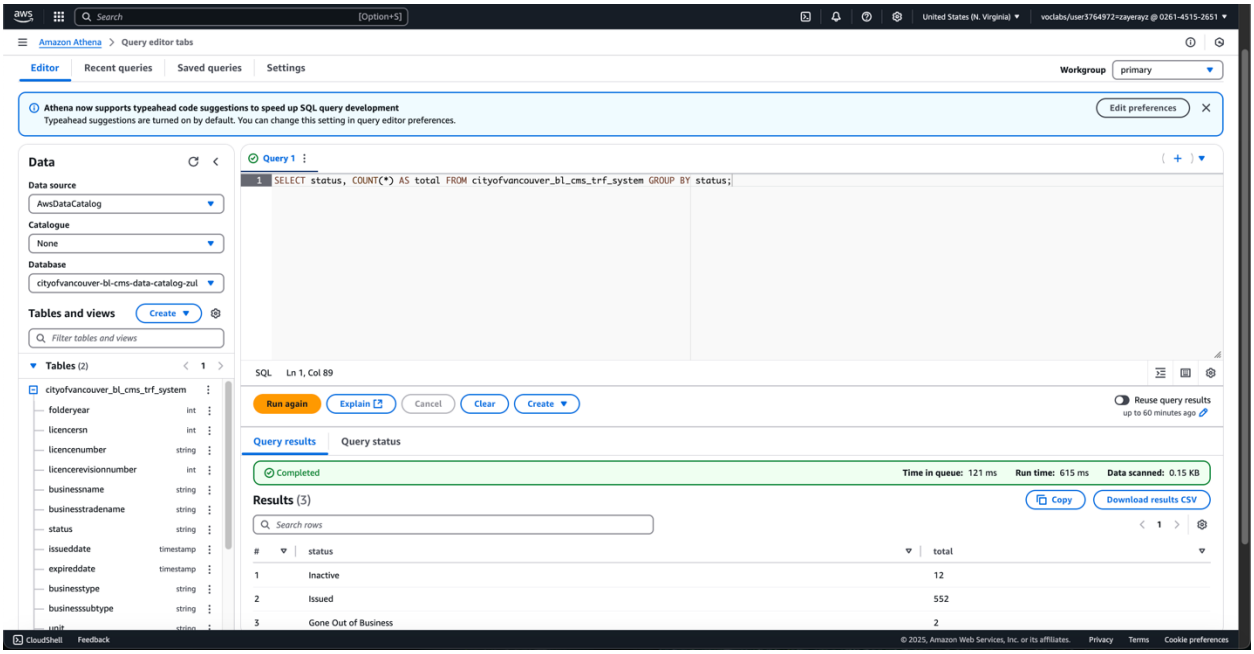


Note. This query returns the most frequent business trade names from the consulting dataset, ordered by license count in descending order. Source: Self-work, AWS Athena Query Editor

Explanation

This one show which business names come most often in the consulting list. I used COUNT to count how many times each name comes. Then I sorted from biggest to smallest. The top one has 324, that's a lot. It helps to know who is most active or popular in this business.

Figure 36: License Status Breakdown – Active vs Inactive



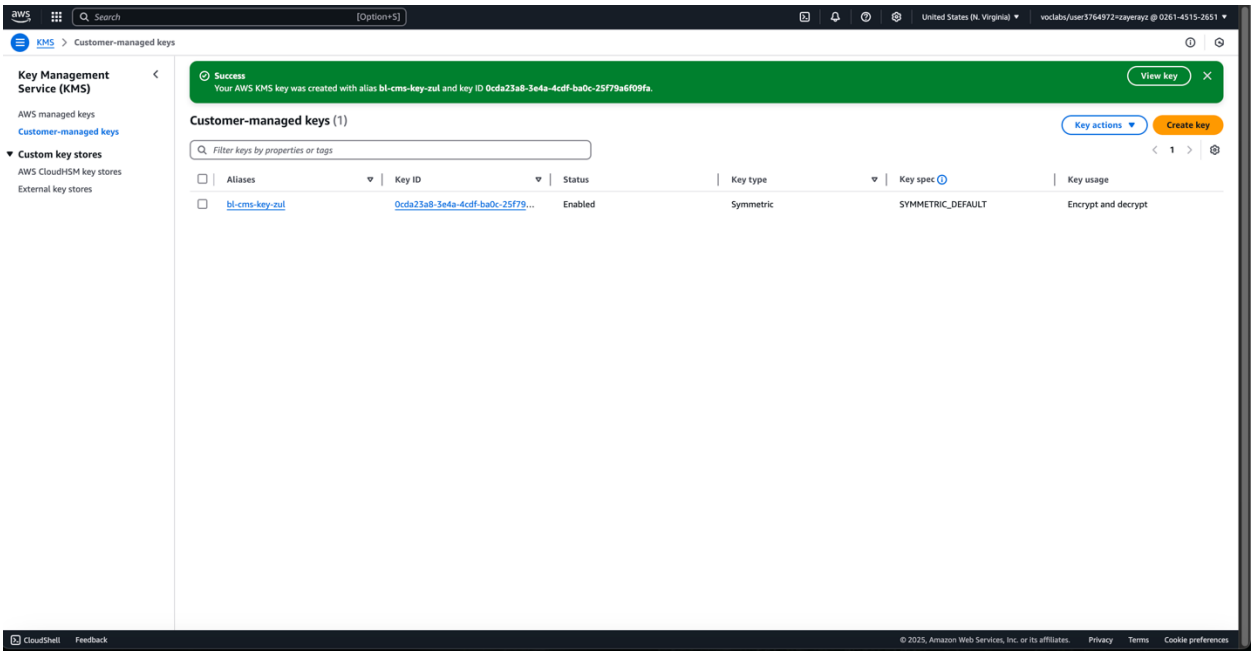
Note. This query shows the distribution of license statuses, including issued, inactive, and gone out of business. Source: Self-work, AWS Athena Query Editor

Explanation

Here I checked how many licenses are active and how many are not. So, I just grouped by status and counted. Most of them are issued (like active), but some are inactive or gone out of business. It's useful to know which ones are still running and which stopped.

Step 6: Data Security

Figure 37: AWS KMS Key Creation – bl-cms-key-zul

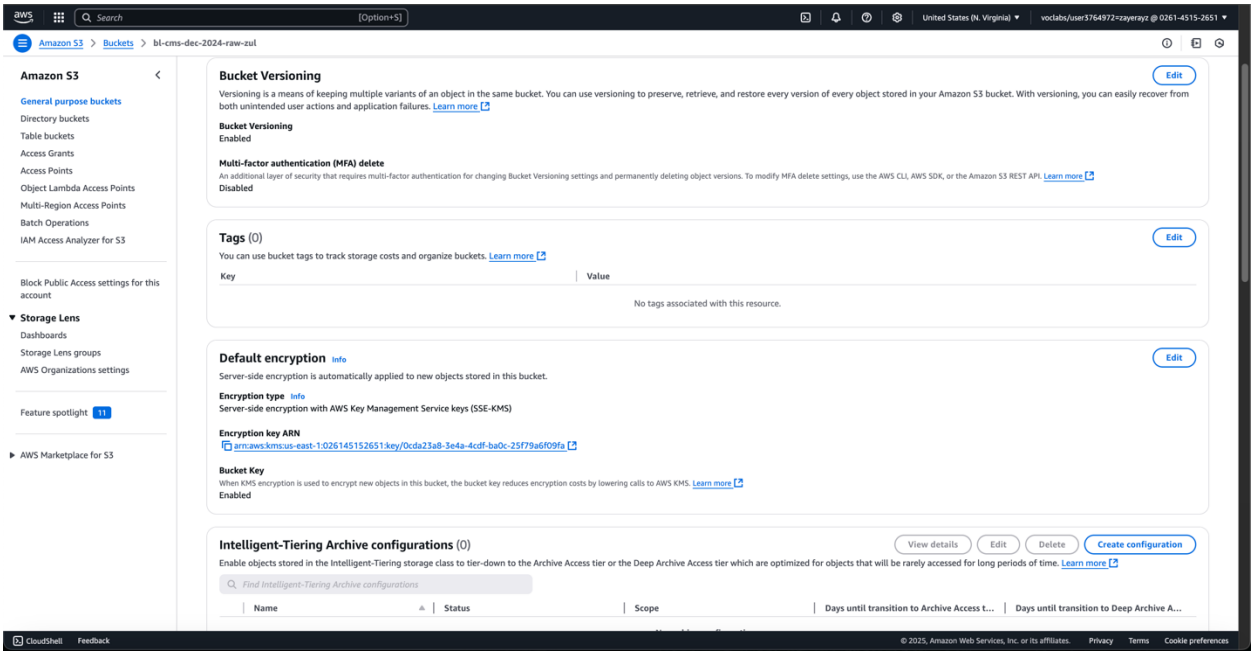


Note. This screenshot shows the KMS key I created in AWS for encrypting S3 data. The key is symmetric and will be used for both encryption and decryption of business license files. Source: Self-work, AWS Key Management Service

Explanation

This is my own KMS key. I make this to lock my files in S3 buckets. I named it bl-cms-key-zul to match my consulting dataset project. It's symmetric so I can use it for both encrypt and decrypt. I will use this in S3 buckets in next steps to make the data secure.

Figure 38: S3 Bucket Encryption and Versioning – Raw Zone

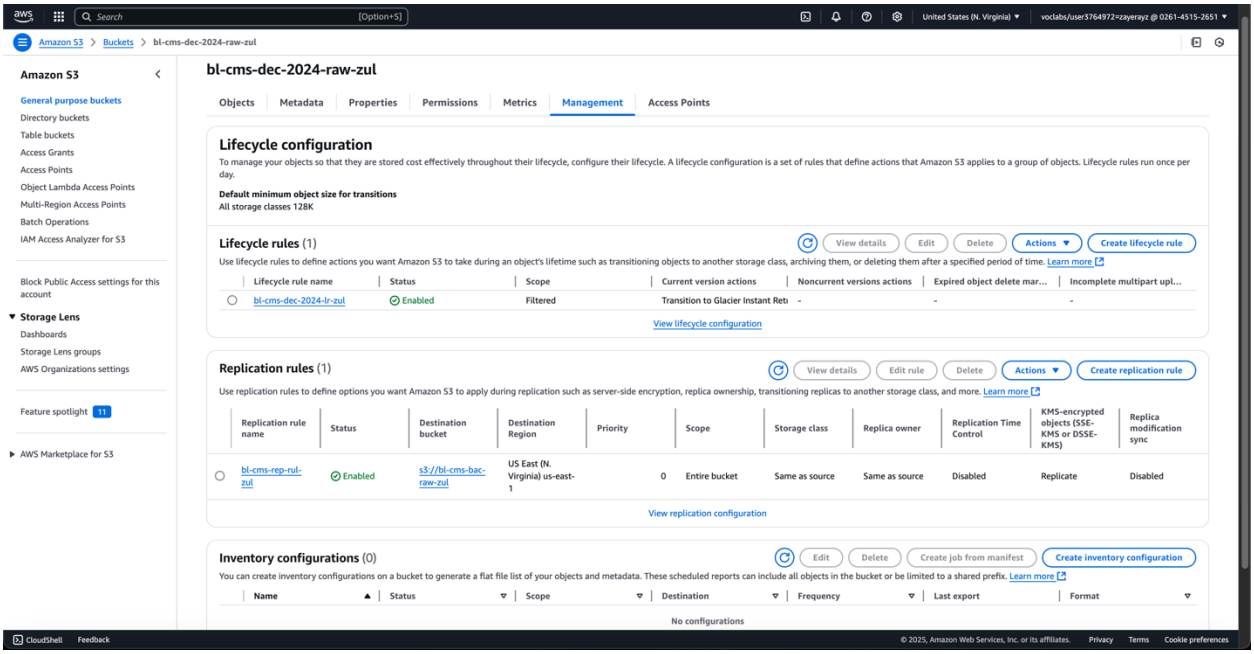


Note. This screenshot shows the settings of my raw S3 bucket bl-cms-dec-2024-raw-zul. I enabled versioning and set default encryption using the KMS key I created earlier. Source: Self-work, AWS S3 Bucket Settings

Explanation

Here I turn on versioning and encryption for my raw bucket. Versioning is for saving old copies if something changes or delete. Encryption is to protect my raw business license files. I select my KMS key to lock them. Now every file I upload here will be safe and can't be read by others.

Figure 39: S3 Replication and Lifecycle Rules for Raw Bucket



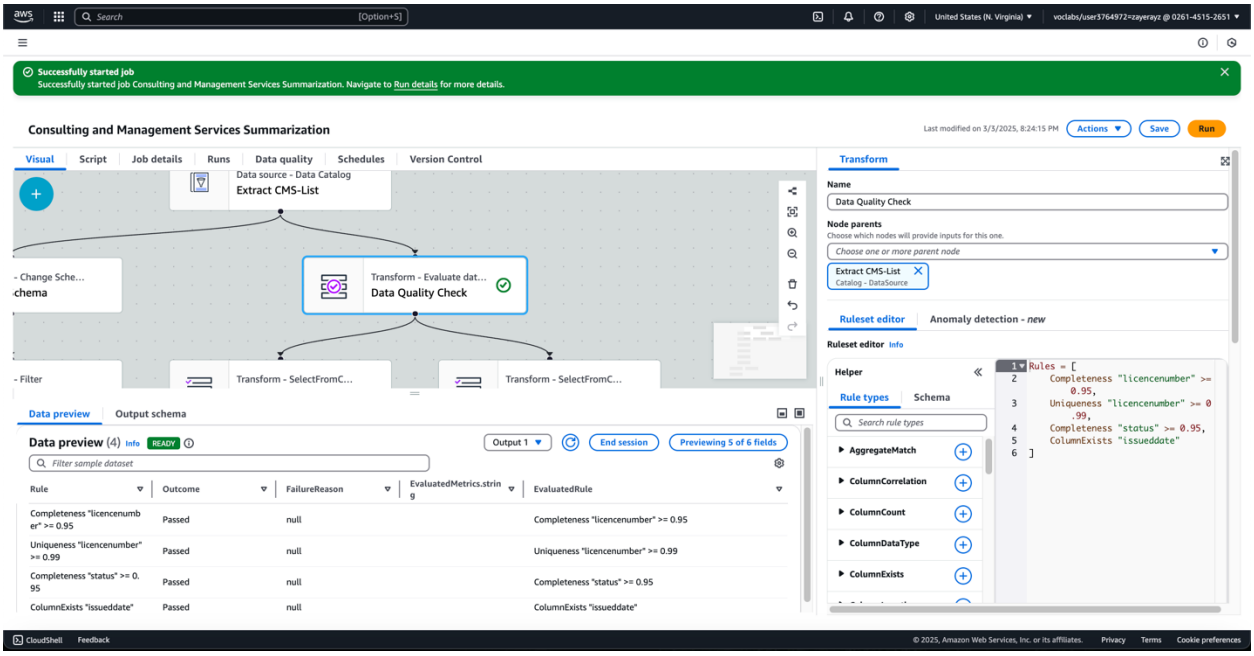
Note. This screenshot shows the replication and lifecycle settings applied to my raw zone bucket. The replication rule sends data to a backup bucket using the same KMS key. The lifecycle rule is used to manage long-term storage. Source: Self-work, AWS S3 Management Tab

Explanation

In this I setup replication from my raw bucket to another backup one. So, my files don't get lost if main bucket got error. I also made lifecycle rule to move old files to glacier storage after some time. It helps to save cost and make system more professional and safer. Replication is using same KMS key I made before.

Step 7: Data Governance

Figure 40: Data Quality Rules, Execution

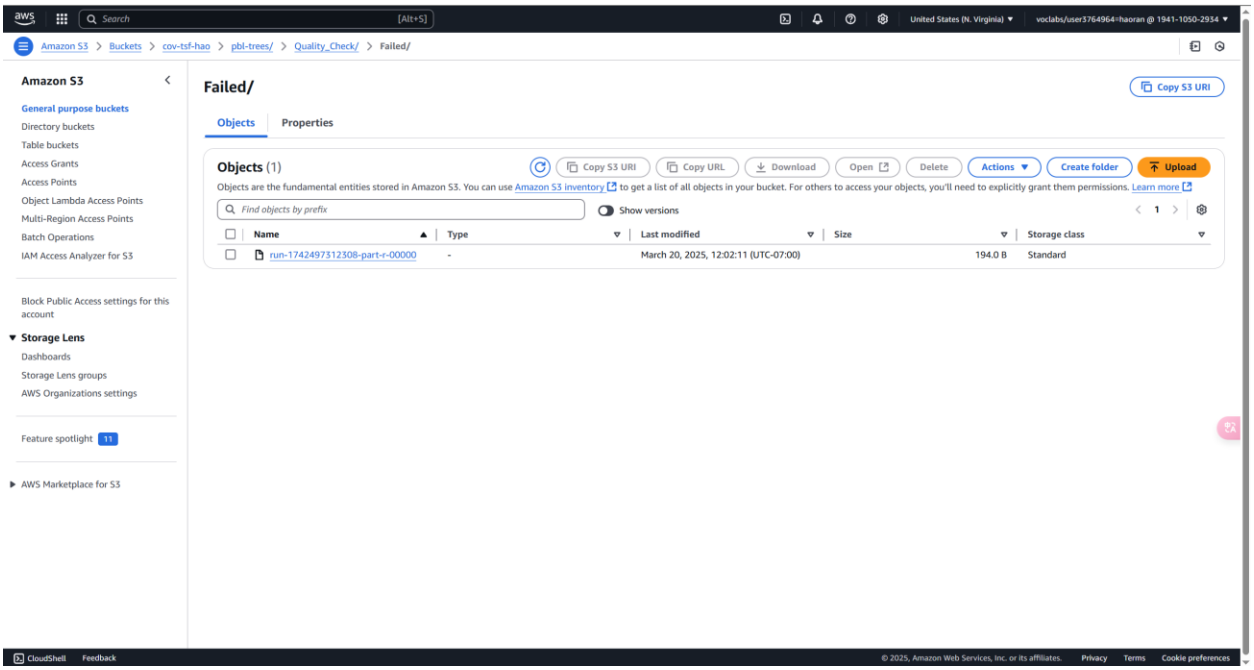


Note. This screenshot shows the main data quality rules I created and executed in AWS Glue Studio. It includes completeness check on “licencenumber” and “status” columns (≥ 95%), uniqueness for “licencenumber” (≥ 99%), and existence check for the “issueddate” column. Source: Self-work, AWS Glue Studio – Data Quality Rule Editor

Explanation

This was the part where I added my data quality check block to the ETL pipeline. I tried to make sure important fields are filled and unique, and check if the column even there. All passed and result came green. I was able to do this part fully, and now data looks ready for next steps.

Figure 41: S3 Output Folder – Failed Results Preview



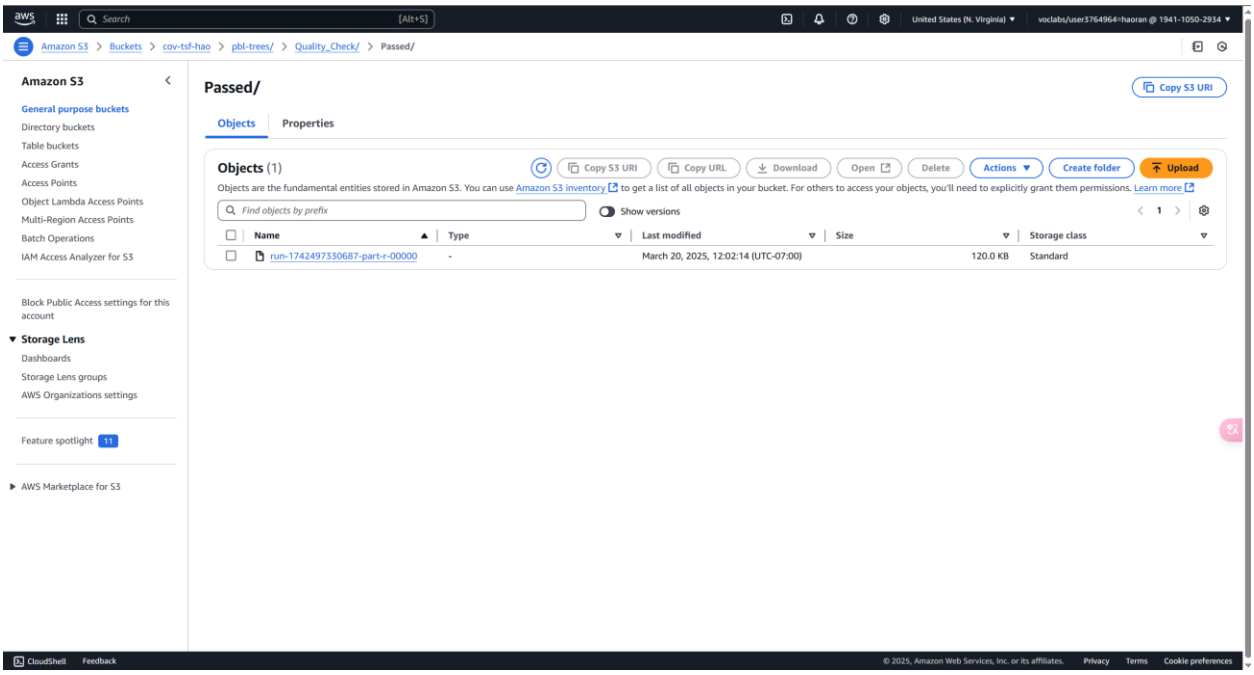
Note. This screenshot shows the Failed folder inside the S3 bucket where failed data quality records are stored. This part was done to separate any data that didn't meet the defined rules.

Source: Peer provided screenshot, AWS S3 – Quality Check Output

Explanation

This part is important to show failed and passed results but honestly, I was struggling here. I couldn't find the right video or remember the exact steps to separate output in passed and failed like this. I understand the logic and how it works, but I couldn't finish it myself so I'm just attaching to show what it looks like.

Figure 42: S3 Output Folder – Passed Results Preview



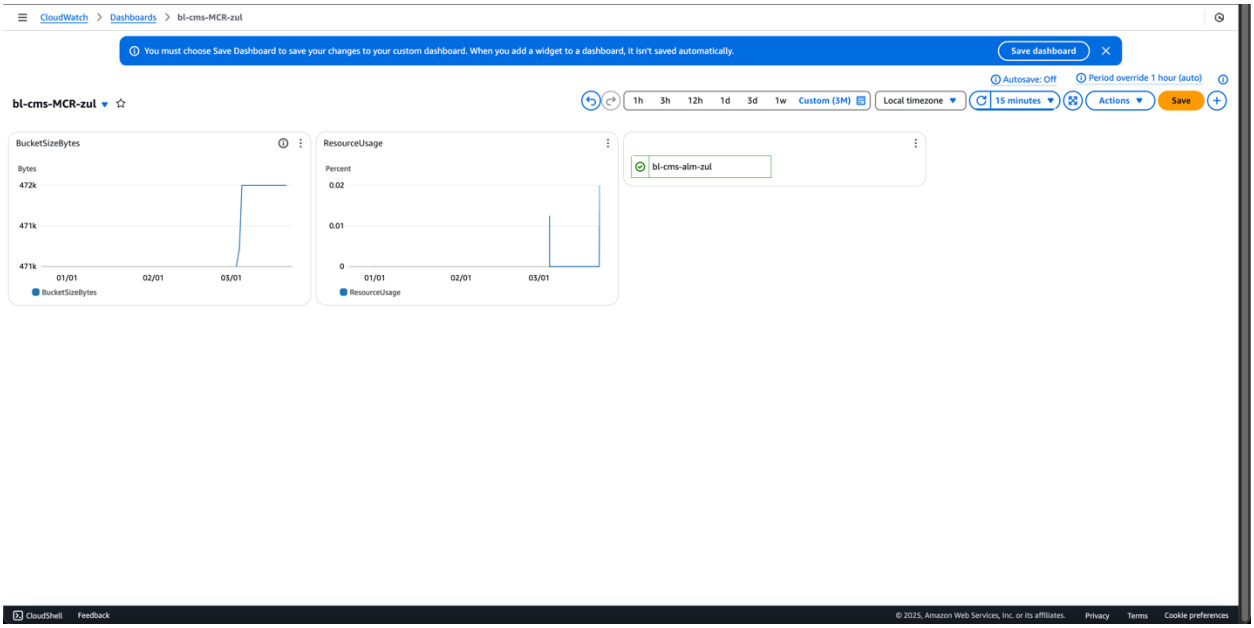
Note. This screenshot shows the Passed folder where records that met all data quality rules were saved. It's part of the validation output done automatically when job is set properly. *Source:* Peer provided screenshot, AWS S3 – Quality Check Output

Explanation

Again, same as before. Just couldn't locate full guide or setup during work session. I understand what's happening in this screenshot and I'll fix mine before final submission. Just showing this to explain I know where it should go.

Step 8: Data Monitoring

Figure 43: Custom CloudWatch Dashboard for Monitoring

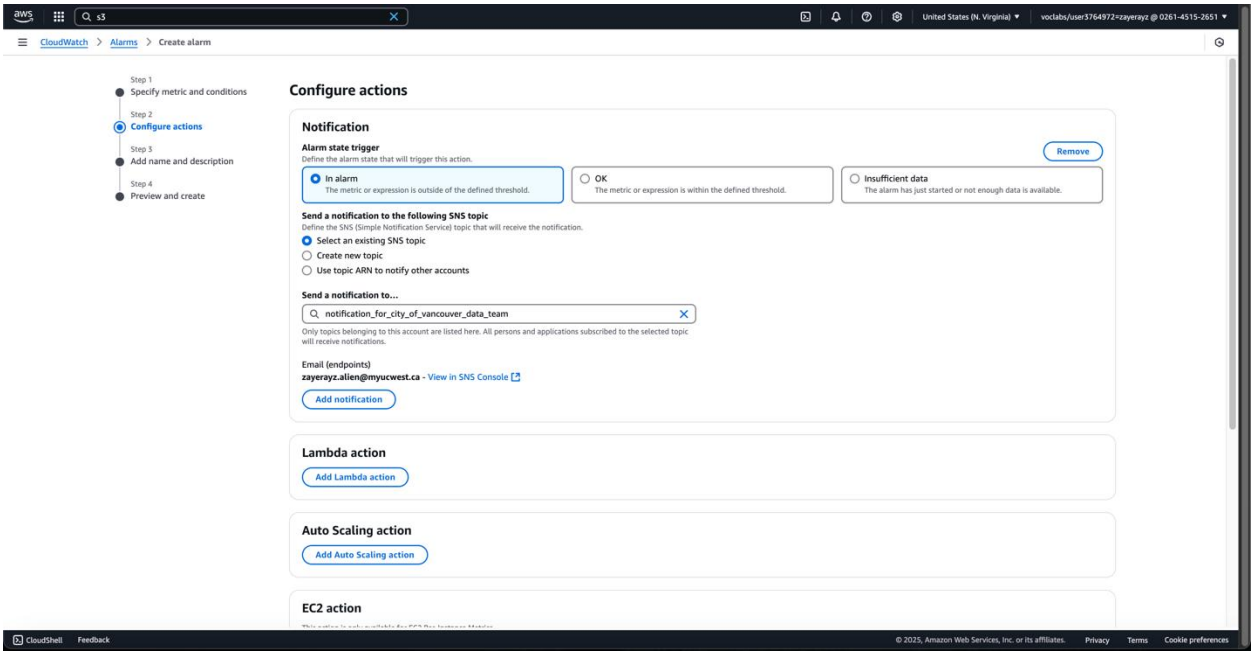


Note. This screenshot shows the custom dashboard bl-cms-MCR-zul with two widgets: one tracking bucket size and another for overall resource usage. *Source:* Self-work, AWS CloudWatch, Dashboards

Explanation

I added dashboard to keep visual on stuff like how much storage I am using and what's happening. I saw bucket size go up in March, which is when I started running my job. It helps to check fast if something crazy happen without opening full AWS pages.

Figure 44: Notification Setup for CloudWatch Alarm

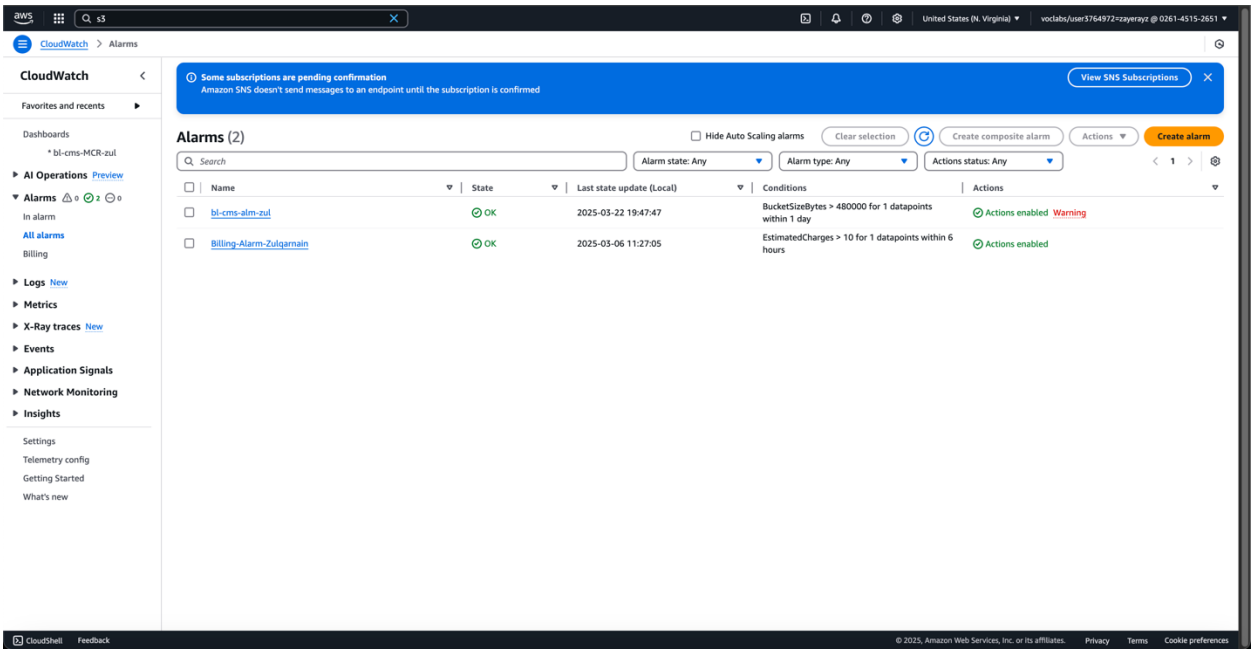


Note. This screenshot shows the setup during alarm creation, with email endpoint zayerayz.alien@myucwest.ca added for receiving bucket alert notifications. *Source:* Self-work, AWS CloudWatch, Alarms, Configure Actions

Explanation

I tried to make email go to me if bucket go above limit. I use topic name like "notification_for_city_of_vancouver_data_team". I click add notification and put my UCW email. Still waiting on confirm I think, but idea is to know if something weird happen.

Figure 45: CloudWatch Alarm Setup – Billing and Storage Thresholds

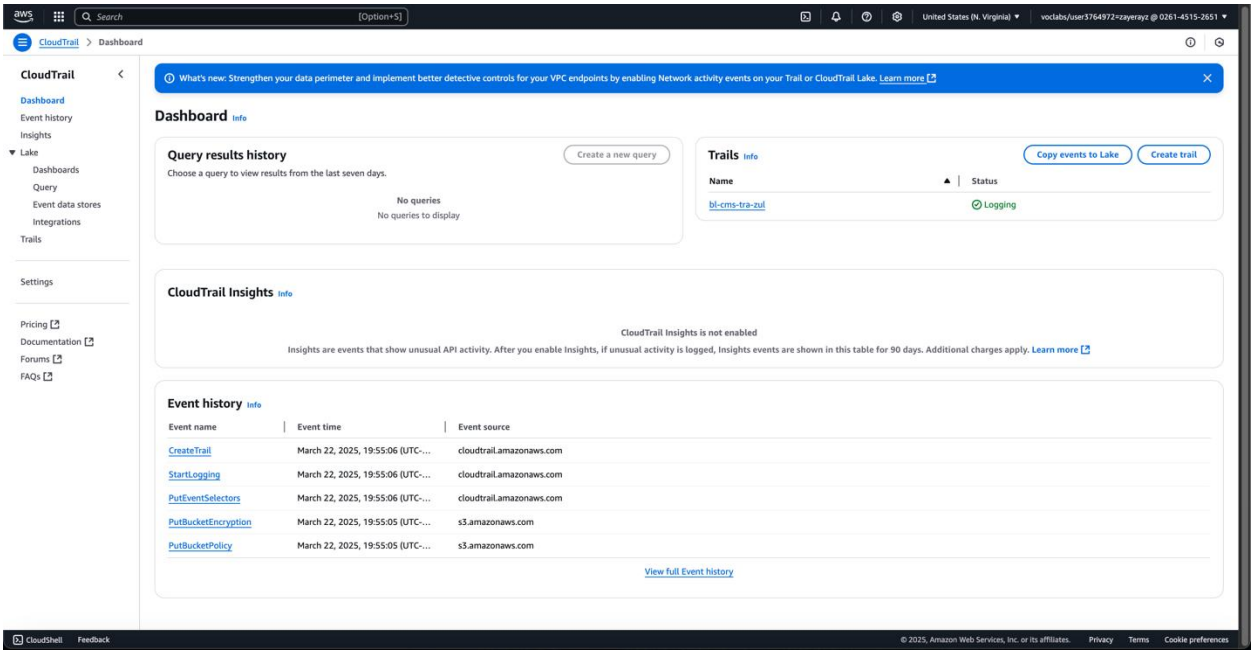


Note. This screenshot shows two CloudWatch alarms set up for my project: one for S3 bucket storage usage (bl-cms-alm-zul) and one for estimated billing cost (Billing-Alarm-Zulqarnain). Both are in OK state and active. *Source:* Self-work, AWS CloudWatch, All Alarms

Explanation:

Here I set one new alarm just to be safe and monitor stuff. First one is for storage, I set it to alert me if my S3 bucket goes above 480,000 bytes in one day. I use that to keep an eye on my storage cost and make sure nothing unexpected is filling up the bucket.

Figure 46: CloudTrail Setup with Logging Events



Note. This screenshot shows the bl-cms-tra-zul CloudTrail trail created with logging enabled. Recent logged events include trail creation and S3 policy updates. *Source:* Self-work, AWS CloudTrail, Dashboard

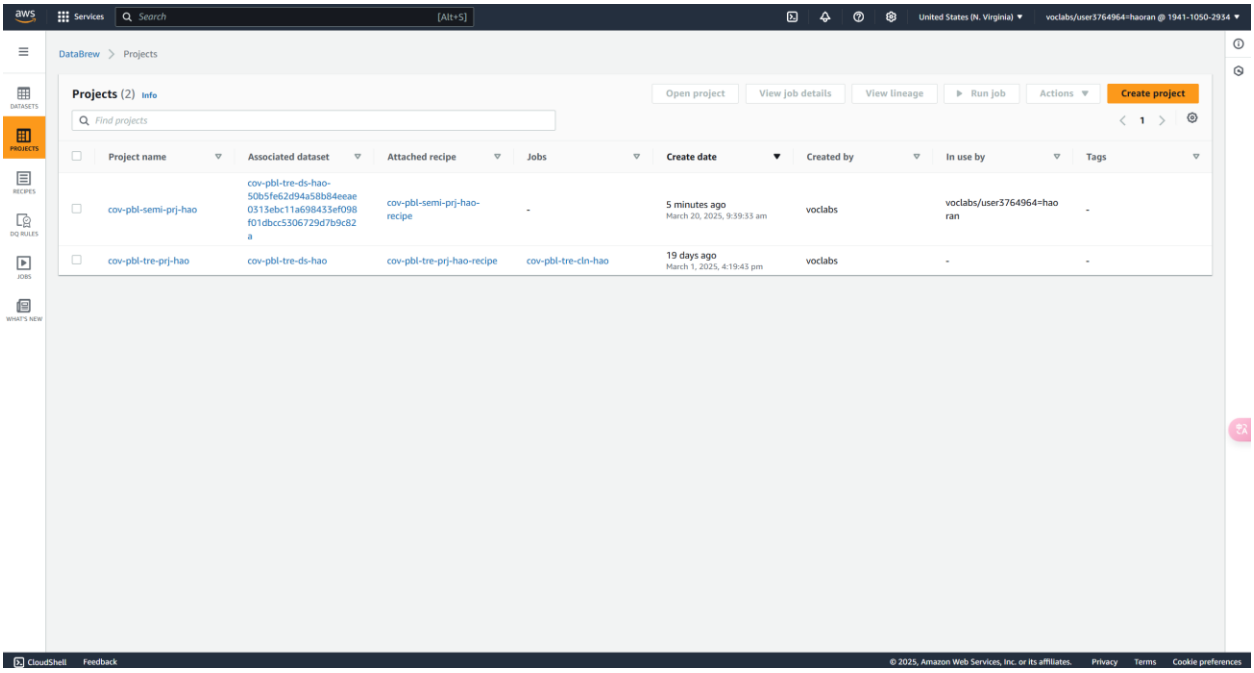
Explanation

Professor, so this is where I set up CloudTrail to track stuff I do in AWS. It shows logs like when I created this trail, turned logging on, added bucket policy, encryption, all that. According to Chat GPT It's not really for querying right now but it's super helpful to see if something weird happen like if someone touch the config or bucket without me knowing. Just keeping track of my own work and for security too. If anything goes wrong, this history helps us to trace back what we did or what someone else did.

DAP Implementation (Individual work – Haoran Xu)

Step 5: Data Analysis

Figure 47: Project Screenshot

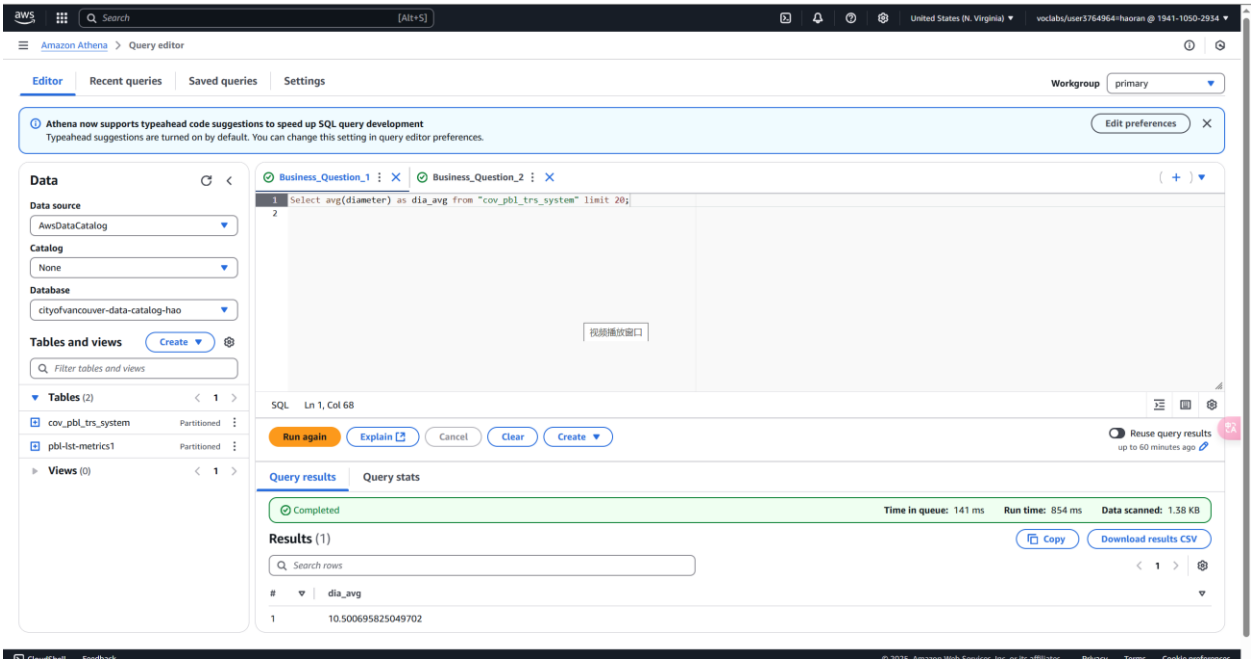


Note. This figure shows the screenshot of the project in AWS Glue Data Brew. Source: AWS Glue

I created the project to check if my dataset has a semi-structured issue. But I found that my dataset is cleaned and can be directly used for analysis.

Now it's time to present the business questions in Athena using SQL.

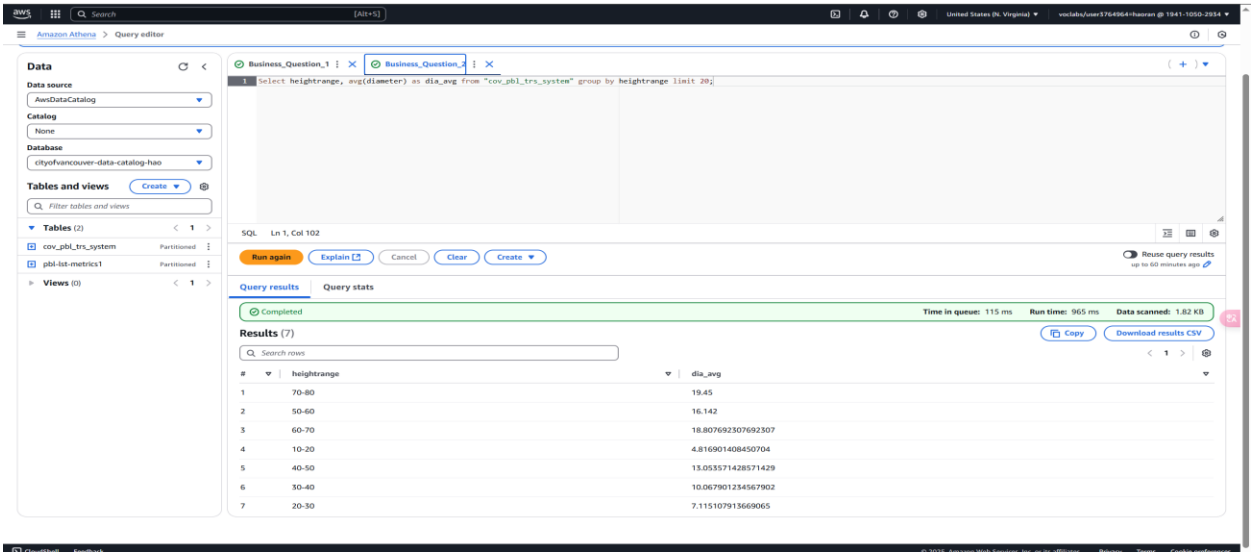
Figure 48: Athena Business Question 1



Note. This figure shows the screenshot of the business question 1 in Athena. Source: Athena

The first business question is simple, it will ask for calculating the average of diameter for the first 20 rows data. And make the output column named “dia_avg”.

Figure 49: Athena Business Question 2

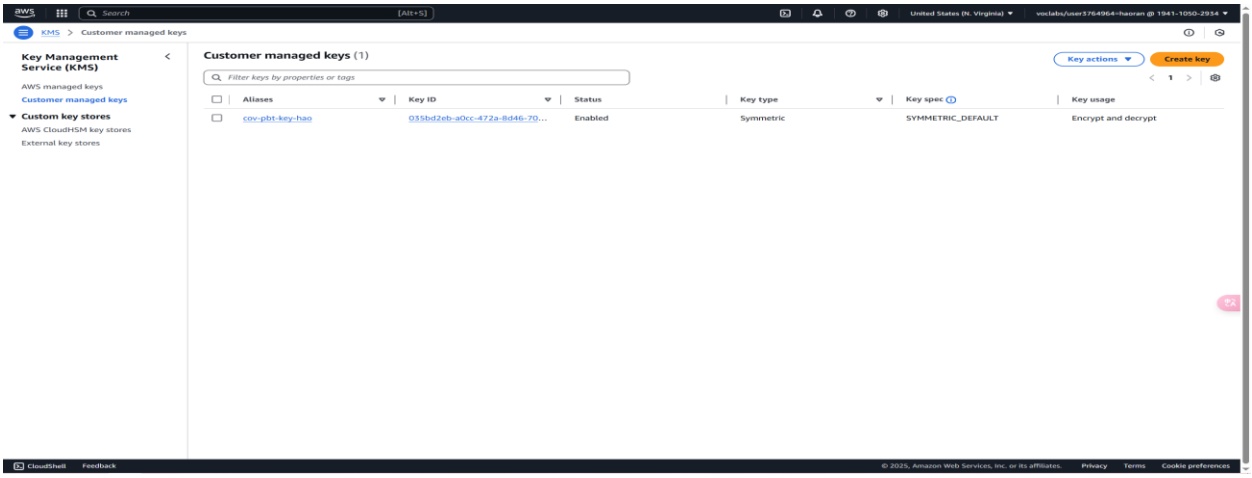


Note. This figure shows the screenshot of the business question 2 in Athena. Source: Athena

The second business question will ask whether the average diameter is directly related to height range under different height_range conditions, and group the output according to height_range. We can conclude from the data that average diameter is indeed correlated with height range and is positively correlated.

Step 6: Data Security

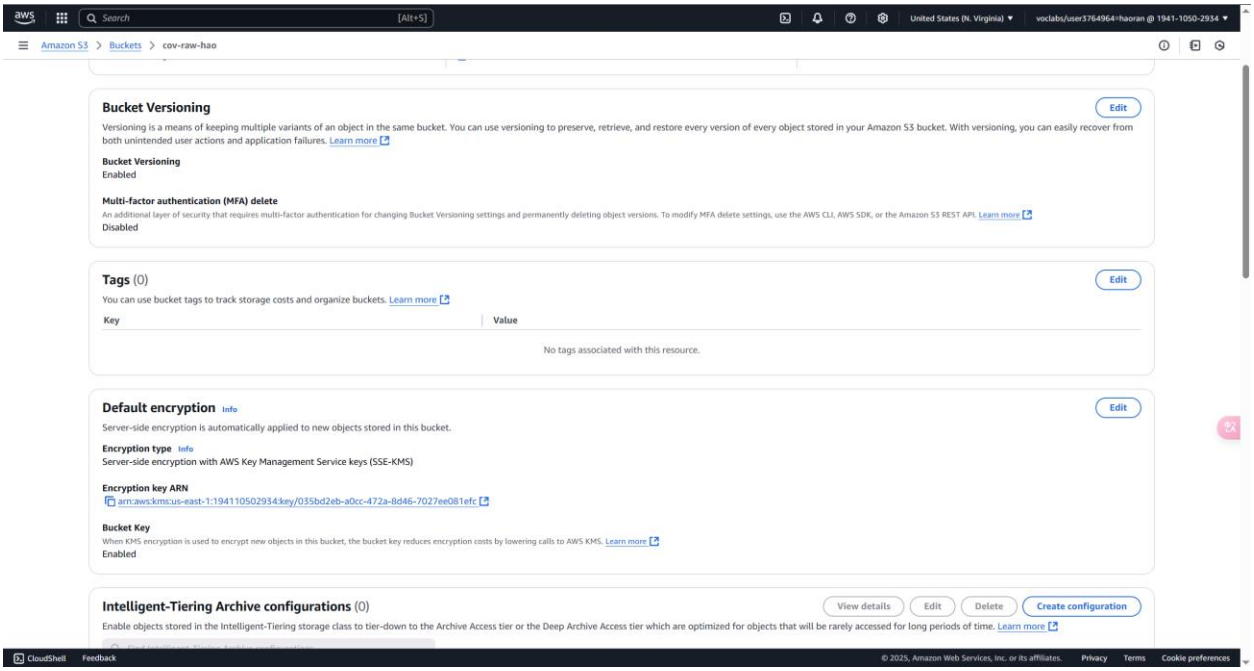
Figure 50: Create KMS Key



Note. This figure shows the screenshot of the key created in AWS KMS. Source: AWS KMS.

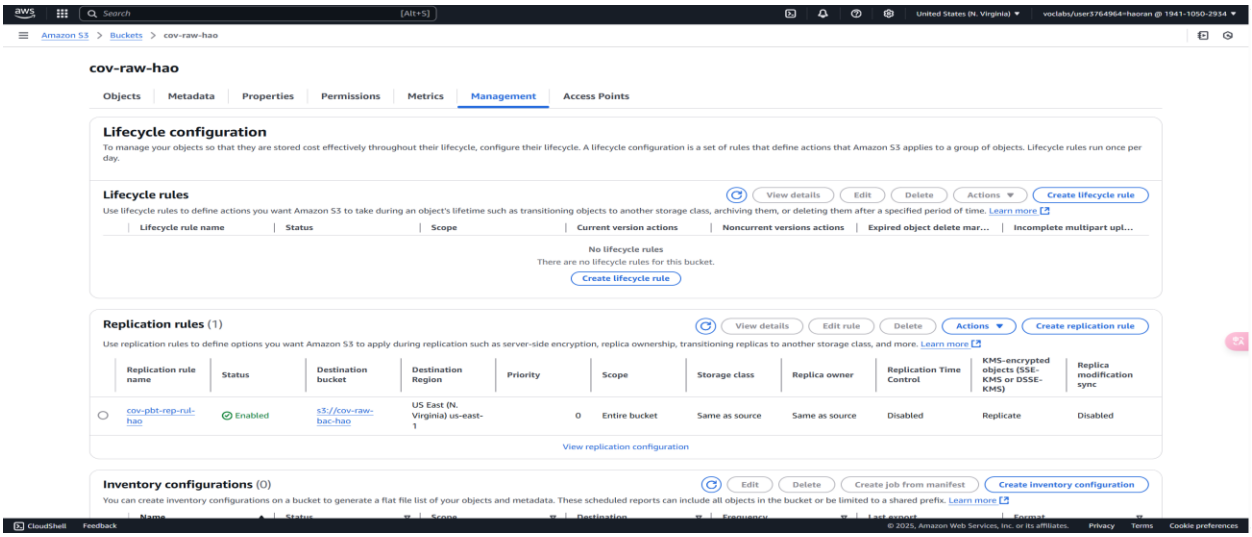
Here, I create a key, it's for sharing with Raw bucket and Transfer Bucket.

Figure 51: Raw-bucket-Versioning and Encryption



Note. This figure shows the screenshot of the versioning and encryption of raw bucket created in S3. Source: AWS S3.

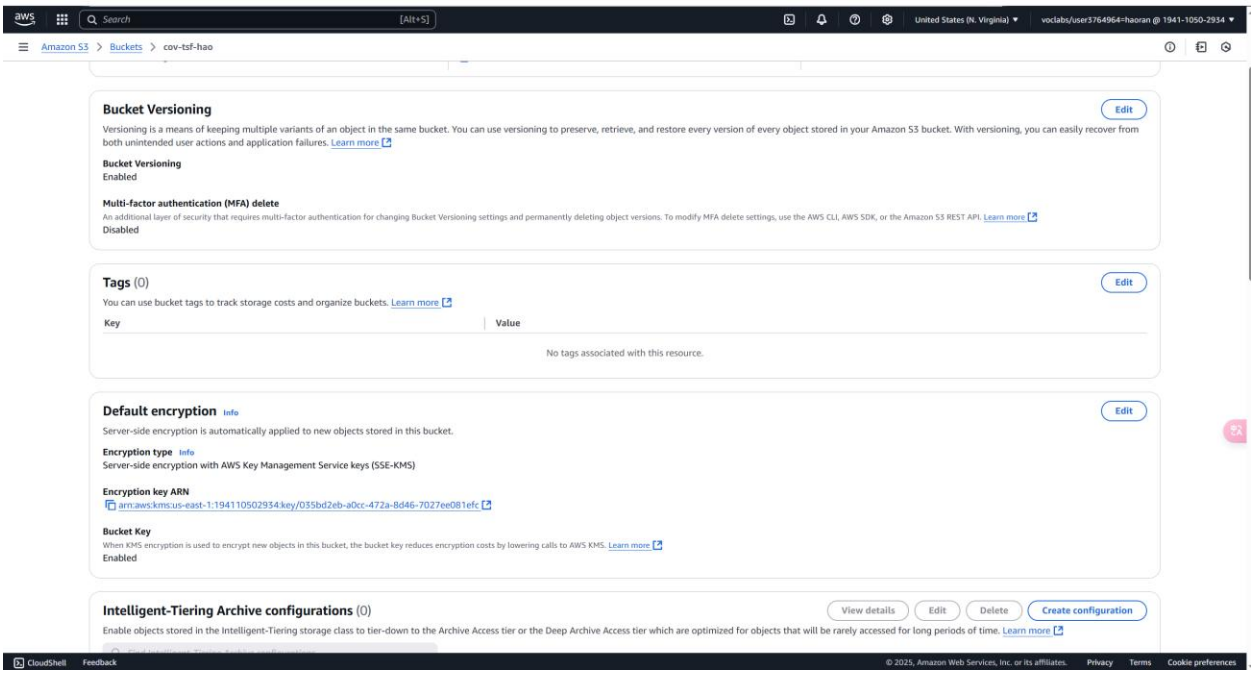
Figure 52: Raw-bucket-Replication Rules



Note. This figure shows the replication rules of raw bucket created in S3. Source: AWS S3.

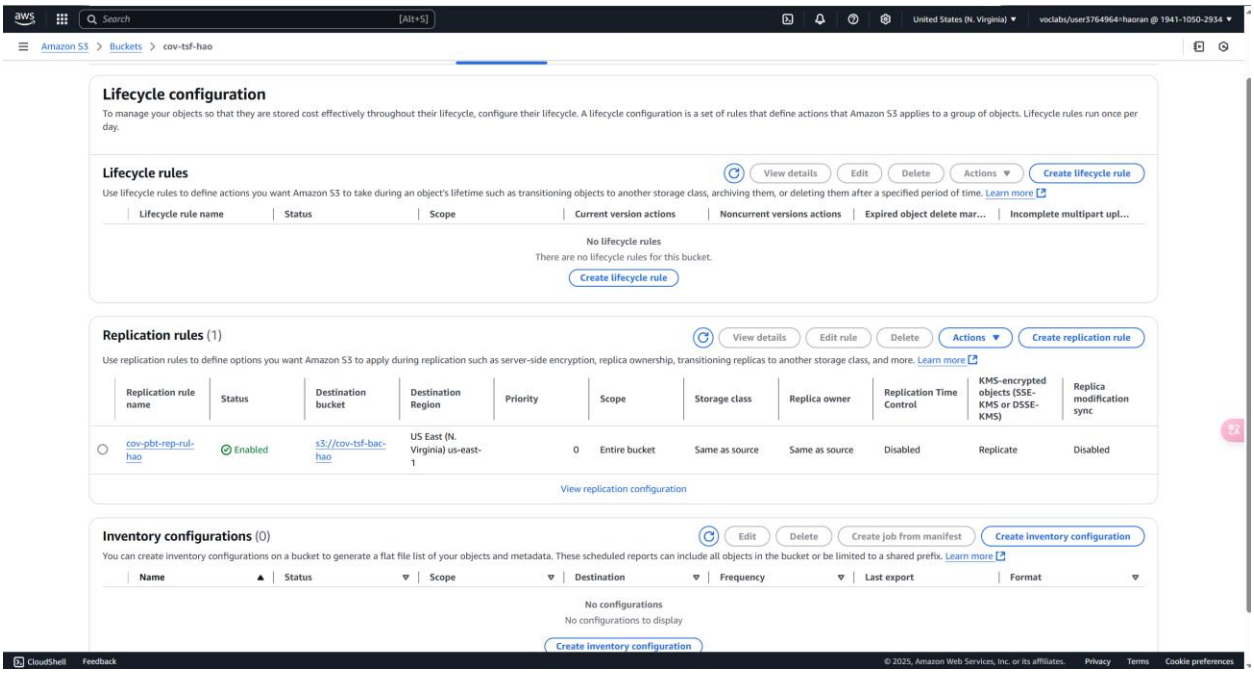
Before this step, I also created the bac-folder for raw bucket in S3. And this is the destination of output.

Figure 53: Transfer-bucket-Versioning and Encryption



Note. This figure shows the screenshot of the versioning and encryption of transfer bucket created in S3. Source: AWS S3.

Figure 54: Transfer-bucket-Replication Rules

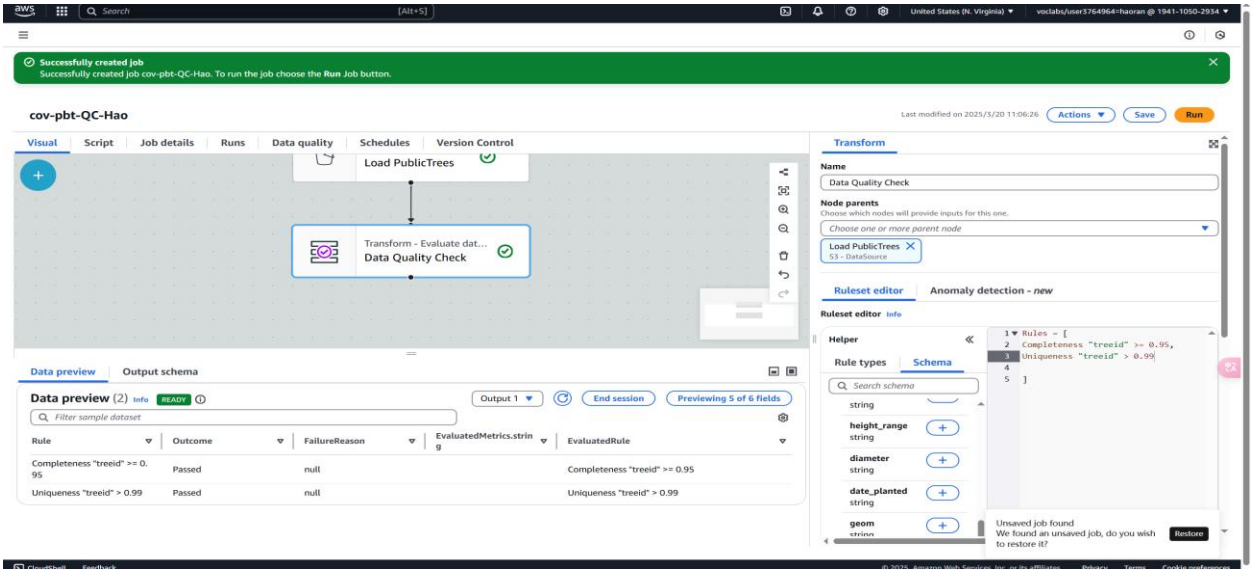


Note. This figure shows the replication rules of transfer bucket created in S3. Source: AWS S3.

Before this step, I also created the bac-folder for transfer bucket in S3. And this is the destination of output.

Step 7: Data Governance

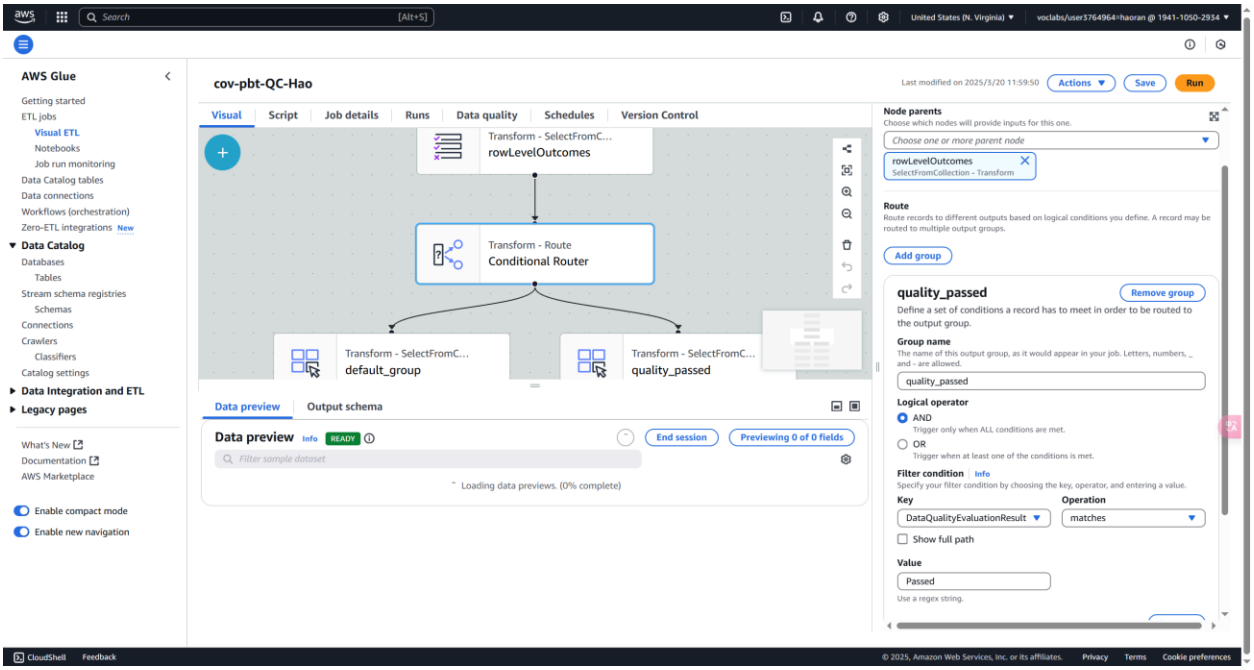
Figure 55: Data Quality Check Rules



Note. This figure shows the screenshot of the data quality check step in visual ETL created in Glue. Source: AWS Glue

In this step, I checked the completeness and uniqueness for “treeid” column. To see if the completeness is equal or greater than 95% and if Uniqueness is greater than 99%.

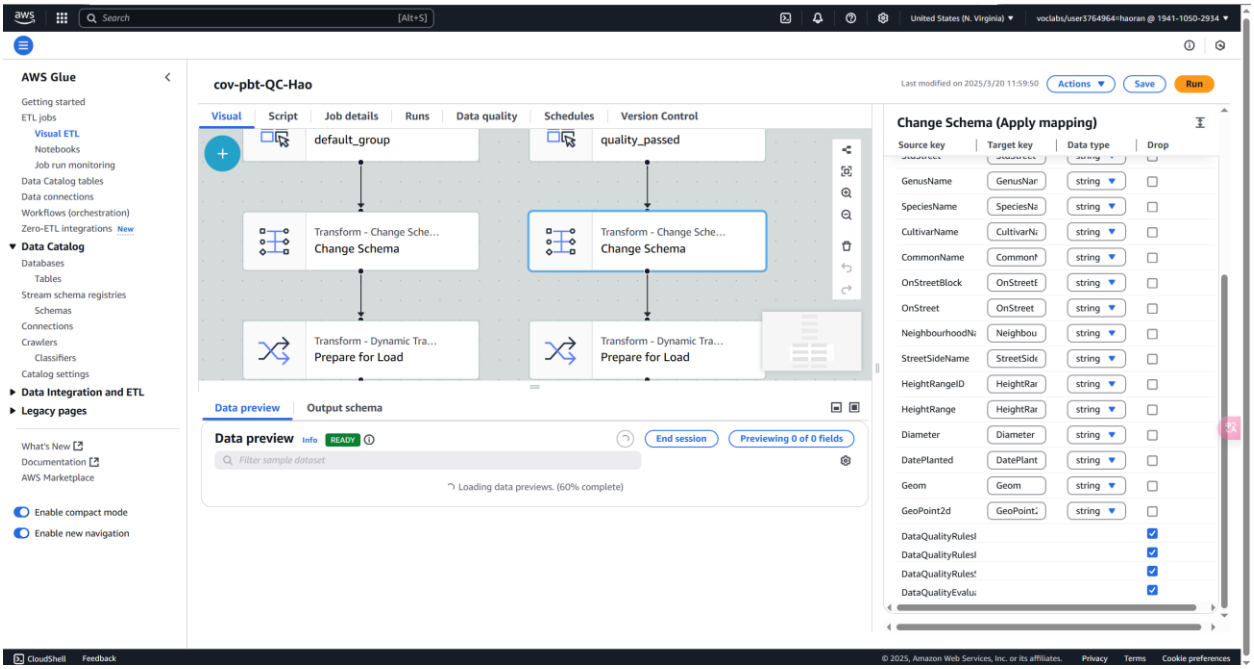
Figure 56: Conditional Router



Note. This figure shows the screenshot of the conditional router step in visual ETL created in Glue. Source: AWS Glue

This step is to separate the quality check output as two files: passed and failed into two different prepared folders.

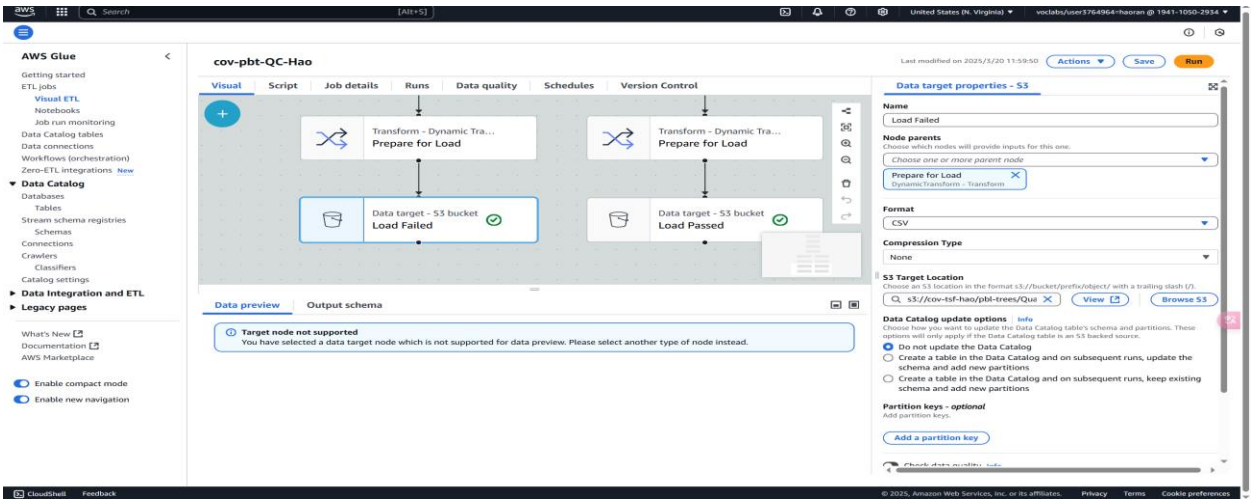
Figure 57: Change Schema Before Load



Note. This figure shows the screenshot of the change schema step in visual ETL created in Glue. Source: AWS Glue

The meaning of this step is to drop the useless columns which are for data quality checking for both passed and failed output files. So it reduces our costs and make the output file looks cleaner.

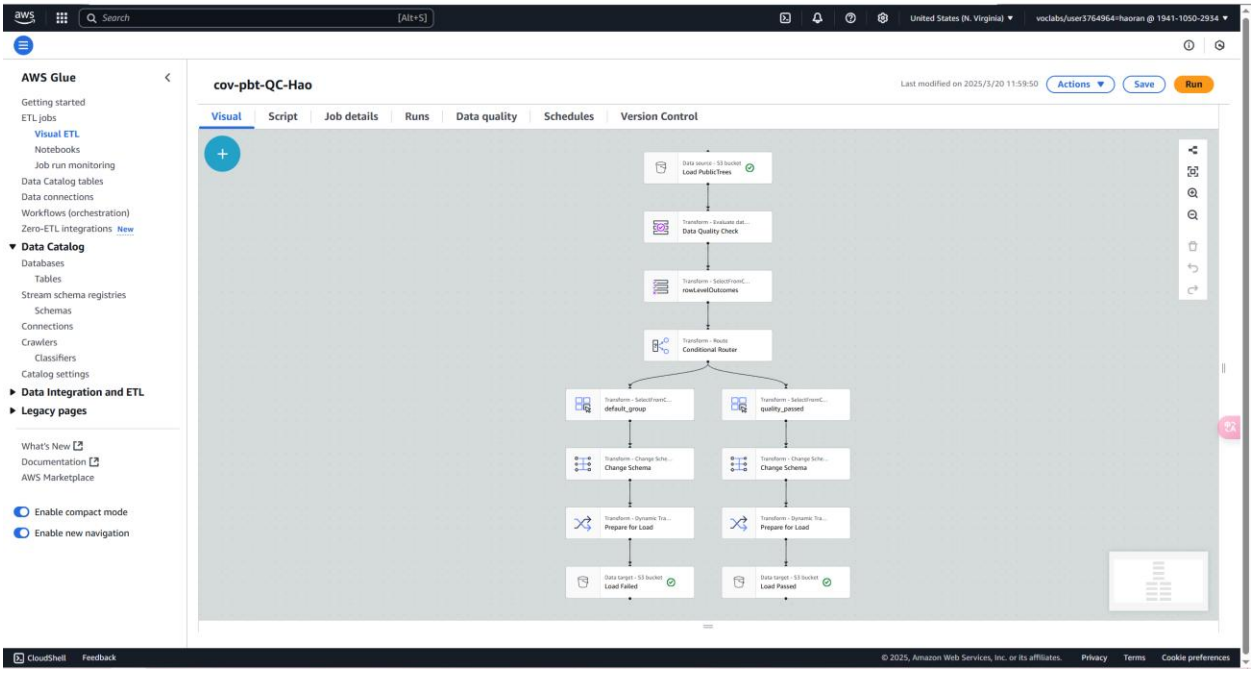
Figure 58: Load Both Passed and Failed into Corresponding Folders



Note. This figure shows the screenshot of the Load Failed/Load Passed step in visual ETL created in Glue. Source: AWS Glue

These two steps are the last step before running the visual ETL. We select the output file format as csv and choose the specified location to output.

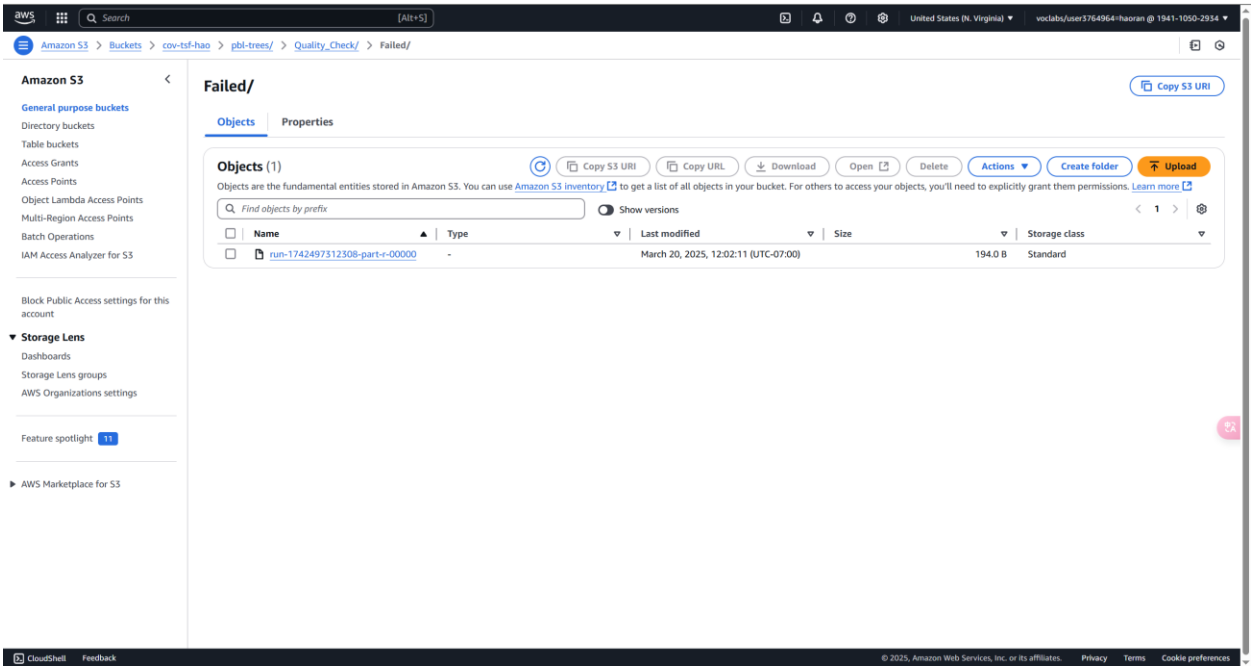
Figure 59: Overall Look of Quality Check Visual ETL



Note. This figure shows the screenshot of the overall look of Quality Check Pipeline in visual ETL created in Glue. Source: AWS Glue

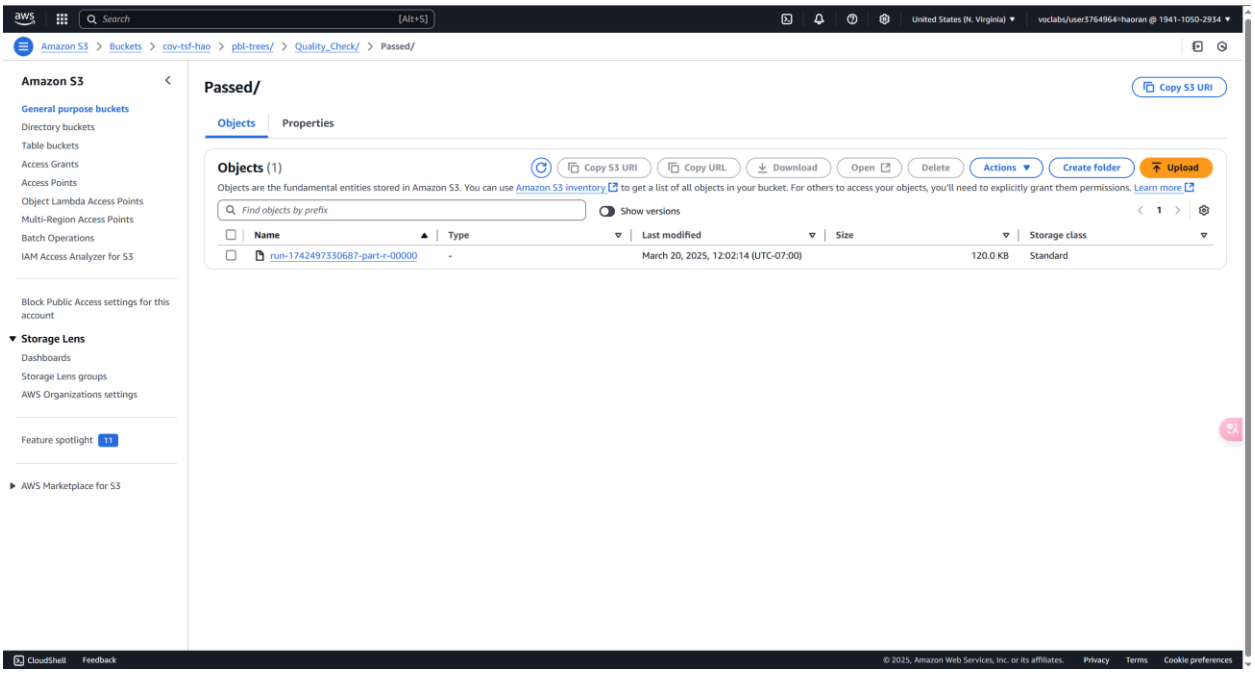
This is the overall look of the Quality Check Visual Pipeline. We can see which part of dataset passed/failed the quality check in the S3 bucket below.

Figure 60: Quality Check Failed Output



Note. This figure shows the screenshot of the Failed output in Transfer Bucket of S3. Source: AWS S3

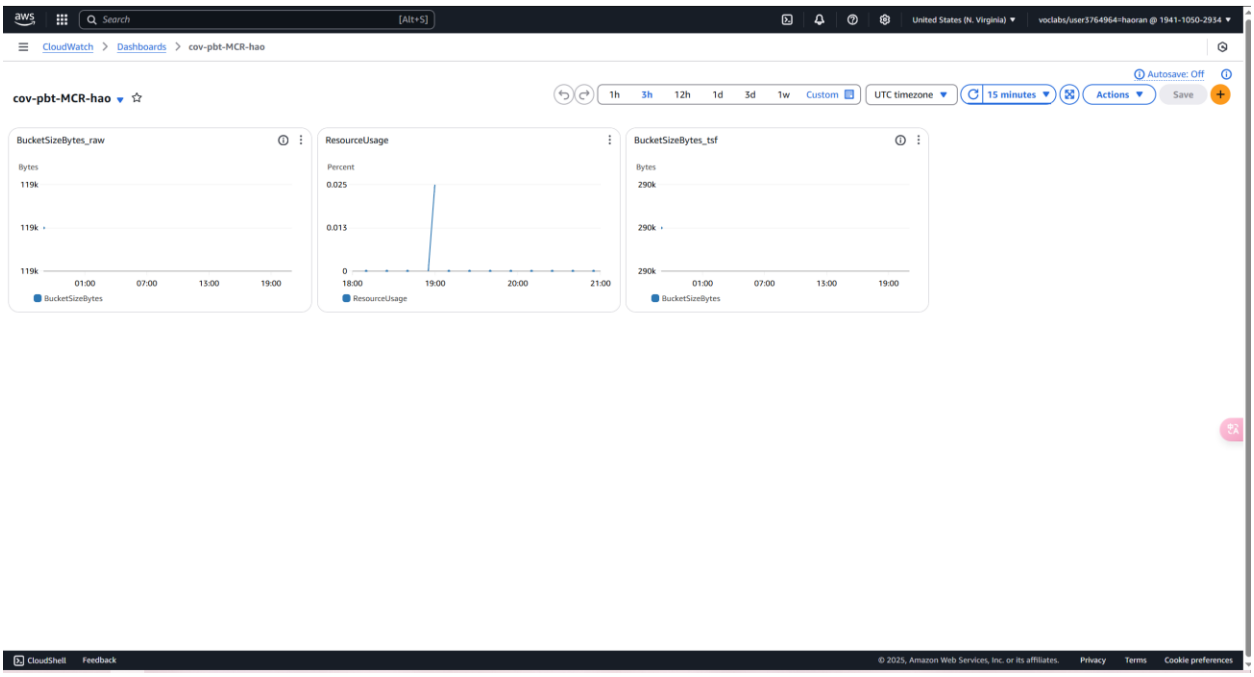
Figure 61: Quality Check Passed Output



Note. This figure shows the screenshot of the Passed output in Transfer Bucket of S3. Source: AWS S3

Step 8: Data Monitoring

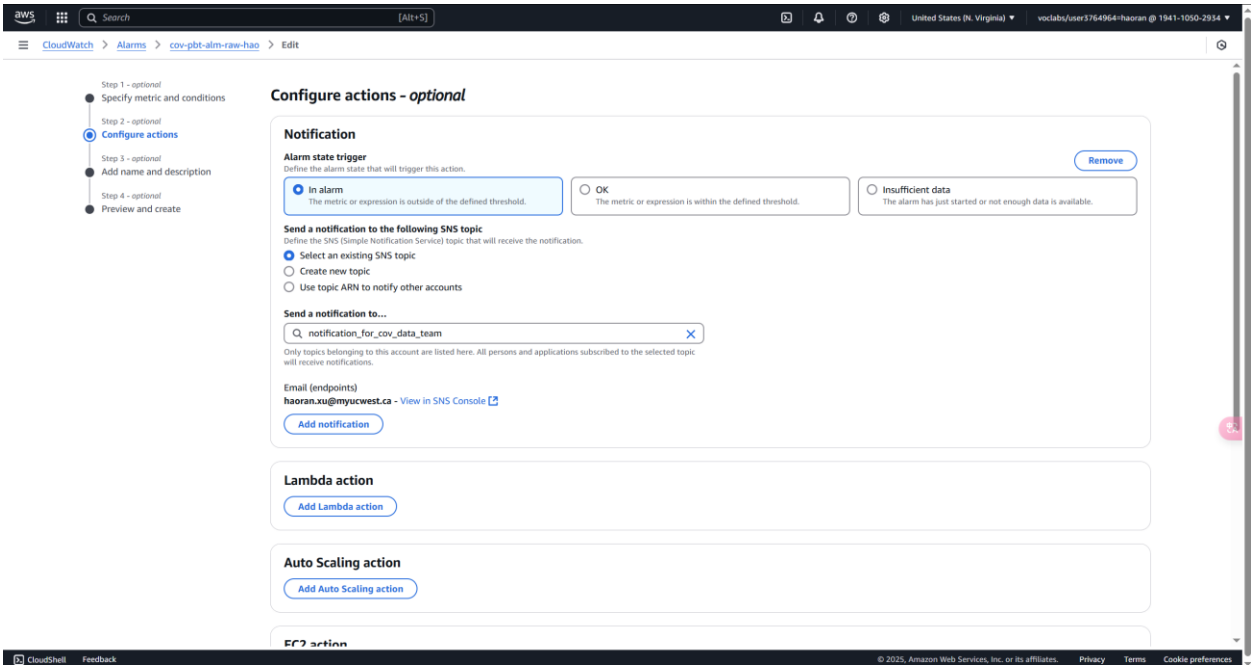
Figure 62: Dashboard of CloudWatch



Note. This figure shows the screenshot of the dashboard created in CloudWatch. Source: AWS CloudWatch

It's for monitoring the usage of raw bucket size, job run resource usage and usage of transfer bucket size.

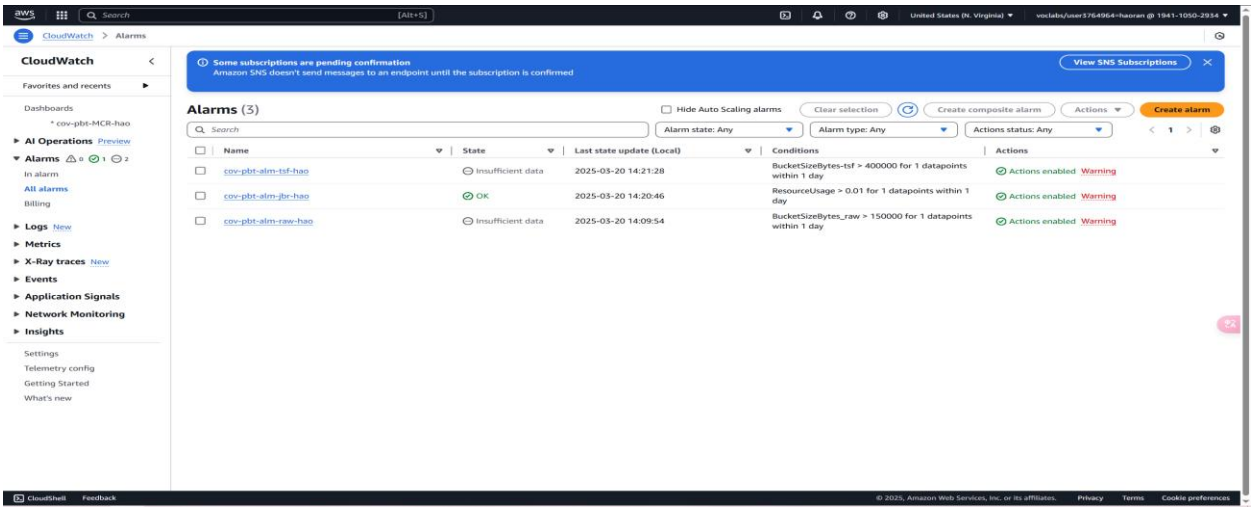
Figure 63: Alarm-Create New Topic for SNS



Note. This figure shows the screenshot of creating new SNS topic in CloudWatch. Source: AWS CloudWatch

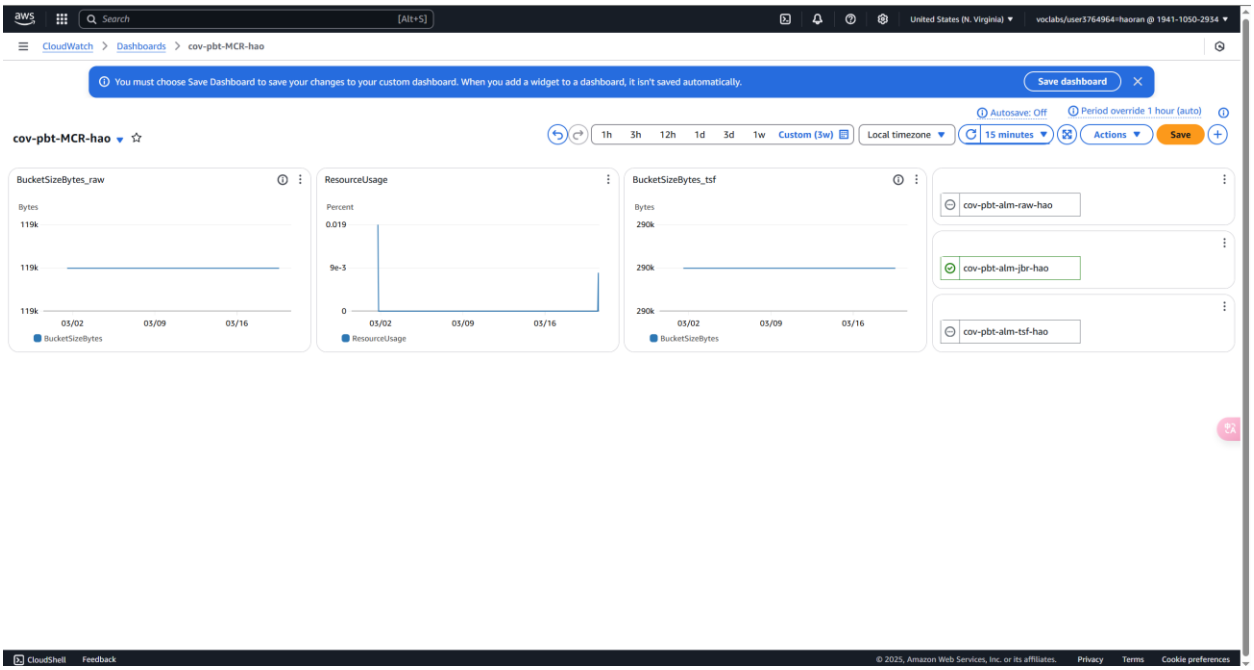
Here, I'm creating Alarm to monitoring the usage of three metrics. If the usage exceed specific amount that I set, I'll get the alarm message from AWS CloudWatch to notify me through email, so I can do some adjustment.

Figure 64: Three Alarms Screenshot



Note. This figure shows the screenshot of all alarms in CloudWatch. Source: AWS CloudWatch

Figure 65: Adding Alarms into the Dashboard



Note. This figure shows the screenshot of all alarms added into the dashboard in CloudWatch. Source: AWS CloudWatch

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DAP Architecture Analysis (Teamwork)

Operational Excellence *(Haoran)*

Operational excellence is definitely a very important part when running DAP. Effective operational excellence management can enable various projects to operate effectively, and the main responsibilities are to create, monitor and maintain the operation of the system. At the beginning of Project 1, we downloaded data from the City of Vancouver data portal to prepare raw data. Here we found and created the raw dataset. After that, we went through profiling and

cleaning steps to ensure that our data was ready to use before transfer. Here, our role in operational excellence is to ensure the integrity and cleanliness of the dataset, paving the way for subsequent use by the data team. We also need to monitor the system in daily use, which can be reflected that all our steps on AWS were recorded, which ensured that modifications were traceable. This helped us ensure system stability and data integrity in our operational excellence. At the same time, Project 2 does not require us to use cloud trail to monitor various actions. However, this is very helpful to ensure operational excellence. If we encounter problems or failures, we can find the problems from the past log history and learn from them to improve the system. We also need to adjust our operating environment and strategies at any time according to customer needs and changes in the business environment. This is also an important part of ensuring effective operational excellence.

Security *(Muhammad)*

In our group project, we all worked with our own datasets and cloud environments, but we followed the same architecture guidelines and AWS best practices. So even though we planned things together, every one of us set up and implemented security individually. This section summarizes how each team member handled security in their own setup.

• **Kyle** worked on the *Vancouver Street Trees* dataset. He created his own KMS key and encrypted his buckets, enabled versioning, used CloudTrail for auditing, and set up alarms for billing thresholds. He also ran transformation jobs in Glue and used Athena for querying.

• **Haoran** used the *Parking Tickets* dataset. His environment included encrypted buckets with KMS, CloudTrail logs, S3 replication for backup, and detailed Glue pipelines with multiple transformations. He also had a separate bucket for storing processed data and applied logging and monitoring.

• **Gyanvi** worked with the *Animal Control Inventory* dataset. She also created her own KMS key, enabled S3 versioning, and configured lifecycle rules, CloudTrail logging, and CloudWatch monitoring. She created her Glue jobs and followed the same structure.

• **Zulqarnain** used the *City of Vancouver Business Licenses* dataset. He created a custom KMS key, encrypted all S3 buckets, enabled versioning, used lifecycle rules, and set up CloudTrail for tracking. He also made CloudWatch alarms for usage and billing and enabled SNS email notifications.

All of us implemented our own identity control using IAM and CloudTrail. We didn't share IAM roles or users each person had their own environment to manage. No EC2 instances were used, so most of our security work focused on S3, Glue, CloudTrail, and CloudWatch.

Implement a Strong Identity Foundation

Did we use it? Yes

How: Everyone used CloudTrail to track activity and manage identity access in their own AWS accounts. IAM permissions were applied based on the least privilege principle. No shared accounts or public access.

Enable Traceability

Did we use it? Yes

How: All of us enabled CloudTrail and used it to track every action in AWS. We also set up CloudWatch alarms. For example, Zulqarnain and Kyle monitored billing and S3 activity with custom alarms.

Apply Security at All Layers

Did we use it? Yes

How: We applied encryption, versioning, and blocking public access to all S3 buckets. CloudTrail monitored user actions. CloudWatch helped track S3 storage and Glue job activity.

Automate Security Best Practices

Did we use it? Yes

How: Everyone configured alarms in CloudWatch. Zulqarnain added SNS for email alerts. Although no auto-remediation was used, our alerts helped us respond faster.

Protect Data in Transit and at Rest

Did we use it? Yes

How: All S3 buckets were encrypted with KMS keys. CloudTrail logs were stored in encrypted buckets too. This covered both transit (data moving across services) and at rest (data in storage).

Keep People Away from Data

Did we use it? Yes

How: CloudTrail logs and datasets were encrypted and not directly accessed. Glue jobs processed the data, and logging was automatic, reducing manual exposure.

Prepare for Security Events

Did we use it? Yes

How: We didn't run a full incident simulation, but CloudTrail logs and CloudWatch alarms gave us a solid setup to catch anything unusual. If something went wrong, we would know right away.

Table 1: Security Summary Table

Security Pillar	Did we use it?	How it was applied
Implement a Strong Identity Foundation	Yes	IAM and CloudTrail used by everyone individually
Enable Traceability	Yes	CloudTrail logs + CloudWatch alarms
Apply Security at All Layers	Yes	S3 encryption, versioning, monitoring
Automate Security Best Practices	Yes	Alarms + SNS email alerts
Protect Data in Transit and at Rest	Yes	KMS encryption + secure storage
Keep People Away from Data	Yes	Logs encrypted, no manual access
Prepare for Security Events	Yes	Alerts and logs prepared us for issues

Note: This is the self-made table about the security summary

Reliability *(Muhammad)*

Just like with security, all of us managed our own reliability setup in our own AWS accounts. We followed the same structure, so the monitoring and fault tolerance ideas were the same just applied individually. We didn't use EC2 or advanced networking, but we did rely on S3, Glue, CloudTrail, and CloudWatch to keep things reliable and monitored.

Automatically Recover from Failure

Did we use it? Partially

How: Everyone set up CloudWatch alarms for job failures, billing, and usage. But we didn't use auto-recovery like restarting jobs or scaling resources automatically.

Test Recovery Procedures

Did we use it? No

How: We didn't simulate any failures or test recovery plans. This is something we could add in future projects.

Scale Horizontally to Increase Availability

Did we use it? No

How: We didn't use horizontal scaling or load balancing since we weren't working with EC2 or dynamic web services.

Stop Guessing Capacity

Did we use it? Partially

How: We used CloudWatch to monitor storage and costs, but we didn't scale any services automatically. Glue jobs had retried, which helped a little.

Manage Change in Automation

Did we use it? Yes

How: Everyone used CloudTrail and CloudWatch to track changes. This reduced the need for manual checking.

Table 2: Reliability Questions Overview

Reliability Area	***Did we use it?***	***Notes***
Automatically Recover from Failure	Partially	Alarms set up, but no automatic fixes
Test Recovery Procedures	No	No simulations or recovery drills done
Scale Horizontally to Increase Availability	No	Not applicable for this project
Stop Guessing Capacity	Partially	CloudWatch monitored usage, but no autoscaling
Manage Change in Automation	Yes	All changes logged and tracked with alerts
Service Quotas & Network Topology	No	Not included in our scope

Workload Architecture	Partially	Each setup worked well but lacked redundancy or fault isolation
Change Management - Monitor Resources	Yes	Done using CloudWatch
Change Management - Adapt to Demand	No	No scaling features implemented
Change Management - Implement Change	Yes	Automated monitoring helped manage changes
Failure Management - Data Backup	No	No formal backup strategy set up
Failure Management - Fault Isolation	No	Everything ran in one region/account per person
Failure Management - Withstand Failures	No	No failover or load balancing done
Failure Management - Test Reliability	No	Didn't test for reliability under failure conditions
Failure Management - Disaster Recovery	No	No disaster recovery plan made

Note: This is the self-made table about Reliability Questions Overview

Performance Efficiency *(Gyanvi)*

Table 3: Performance Efficiency Questions

Performance efficiency questions	**Implemented (Yes/No)**

Selection	
How do you select the best-performing architecture?	No
How do you select your compute solution?	No
How do you select your storage solution?	Yes
How do you select your database solution?	No
How do you configure your networking solution?	No
Review	
How do you evolve your workload to take advantage of new releases?	No
Monitoring	
How do you monitor your resources to ensure they are performing?	Yes
Trade-offs	
How do you use trade-offs to improve performance?	Yes

Note: This is the self-made table about Performance Efficiency Questions

Performance efficiency questions:

1. Selection

1.1. How do you select the best-performing architecture?

We did not implement this specifically as we used the default architecture setup for performance. We can improve by evaluating different architecture based on our requirements and selecting the best-performing one.

1.2. How do you select your compute solution?

We did not create an EC2 instance for our project nor did we choose the auto-scaling option to automatically create EC2 instances based on demand. We can improve by selecting the EC2 instance based on our workload.

1.3. How do you select your storage solution?

We used the S3 standard option for storage in our project, however, Gyanvi implemented a lifecycle rule to switch storage class from standard to Intelligent tiering after 30 days and then to Glacier Instant Retrieval after 180 days to optimize cost. We can improve by exploring more options for storage solutions like EBS for enhancing cost and performance efficiency.

1.4. How do you select your database solution?

We did not implement a database solution in our project. We can improve by using database services like Amazon RDS to optimize performance.

1.5. How do you configure your networking solution?

We did not implement any networking solution configuration. We can improve by using VPC or content delivery networks to enhance performance.

2. Review

2.1. How do you evolve your workload to take advantage of new releases?

We did not evolve our workload to take advantage of the new releases. We can improve by implementing more features offered by AWS to improve performance.

3. Monitor

3.1. How do you monitor your resources to ensure they are performing?

We implemented resource monitoring by using the AWS CloudWatch feature. We created three metrics and three alarms in a dashboard to track billing and CPU usage in real time. We can improve by utilizing enhanced CloudWatch features to optimize performance.

4. Trade-offs

4.1. How do you use trade-offs to improve performance?

We implemented trade-offs using compression techniques like storing system files in parquet format with snappy compression type. However, we can improve by enabling caching for read-heavy workloads or compressing log data to improve performance.

Performance efficiency design principles

1. Democratize Advanced Technologies

We democratised advanced technologies like AWS CloudWatch and CloudTrail which handles monitoring and user activity logging. We did not build any custom solutions for infrastructure management.

2. Go Global in Minutes

We did not deploy our system in multiple AWS regions to reduce latency or improve the global user experience. This was not under the scope of our project.

3. Use Serverless Architectures

We have used many serverless architectures like CloudWatch, and CloudTrail for monitoring and logging user activities.

4. Experiment More Often

We did not perform comparative analysis and experimentation of various storage and computing techniques to choose the best-performing configuration.

5. Have Mechanical Sympathy

We selected the appropriate AWS services such as CloudWatch and CloudTrail for monitoring and logging. We did not deeply analyze data access patterns or optimize databases or storage.

Cost Optimization *(Peng)*

We have already adopted a consumption model for both parts of the project. That is because we paid only for the AWS services that we require based on the requirements of the City of Vancouver rather than using elaborate forecasting. For example, the city of Vancouver clearly requires us to do the data ingestion in part 1 of the project and the data monitoring in part 2 of the project. In this case, we paid only for buckets in S3 and Dashboard and Alarms in CloudWatch. Additionally, we didn't measure overall efficiency, but we operated some functions with the awareness of cost reduction. For example, in part 2 of the project, although we did not measure overall efficiency, we considered the cost and set 1 day for monitoring data for setting alarms. Moreover, we stopped spending money on data center operations in both parts of this project. That is because we mainly focus on the City of Vancouver to proceed with its business projects. Next, we analyzed and attributed expenditure in part 1 of the project but not in part 2 of the project. That is because we have already done the cost estimation for 12 months in part 1 of the project, and our team has an opportunity to optimize the resources and reduce the costs. Finally, we did not technically use managed and application-level services to reduce the cost of ownership in both parts of the project, but we considered the cost reduction when operating

services at AWS. Although we did not technically reduce the operational burden of maintaining servers for tasks such as sending emails or managing databases, we considered the cost when operating services at AWS. For example, we considered the cost and set 1 day for monitoring data for setting alarms, which not only reduced the cost but also managed databases.