Project 6: Calendly Booking Data Analytics

Overview

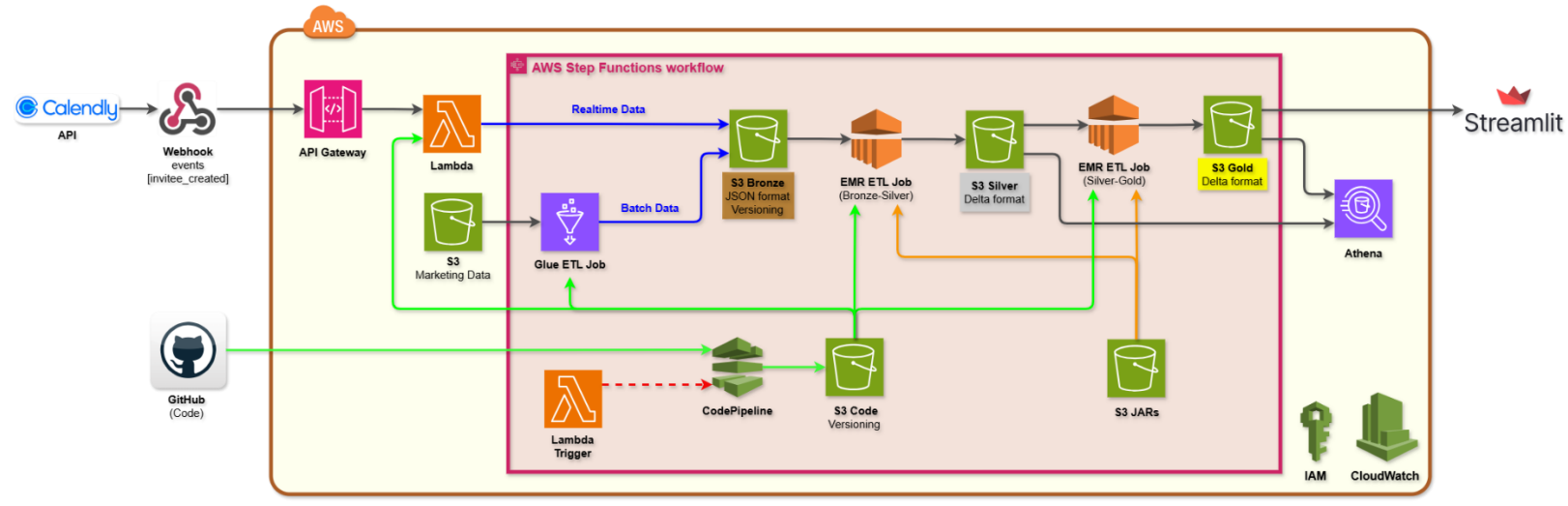
In this project, we work with JSON-formatted data collected from two primary sources: 1) booking (invitee) events from the Calendly platform via Webhooks, and 2) marketing cost data retrieved from a publicly available database stored in the DEA S3 bucket. The goal is to ingest these two data set, integrating them, generate meaningful business metrics, and provide insights that help optimize marketing spend and evaluate campaign conversion rates.

This project implements a hybrid data engineering pipeline that combines real-time, event-driven ingestion (Calendly events) with batch data processing (marketing data). Newly created booking events are captured through Calendly Webhooks, while daily marketing cost data is ingested on a scheduled basis. All data is processed using a fully serverless AWS architecture to ensure scalability, reliability, and cost efficiency.

Real-time booking events are delivered in HTTP format from the Calendly Webhook to an AWS API Gateway endpoint, which triggers a Lambda function. These raw events are stored in the S3 Bronze bucket in their original JSON format. In parallel, an AWS Glue ETL (Spark) job is scheduled to ingest daily marketing cost data from the DEA public S3 bucket (downloadin them in the HTTP format) and store it in a dedicated folder within the S3 Bronze layer.

A Bronze–Silver–Gold data modeling approach is applied to ensure clean, structured, and analytics-ready datasets. Two additional Glue ETL jobs perform data transformation and aggregation, progressively refining the data and loading it into the Silver and Gold S3 buckets. The Gold layer contains curated datasets optimized for analytics and reporting. They are storing the data in the format of Delta Tables.

Finally, Streamlit is used to visualize key business KPIs and performance metrics through an interactive dashboard. AWS CodePipeline automates the deployment process by pulling Python and PySpark scripts from a GitHub repository and deploying them to AWS Lambda and Glue jobs. AWS Glue Triggers handle daily scheduling, while AWS Glue Workflows orchestrate the end-to-end pipeline, resulting in a scalable, modular, and production-ready data architecture aligned with modern data engineering best practices.



Data Schema Definitions (Bronze, Silver, Gold)

🟫 Bronze Layer – Raw Events (Append-Only)

- event_created_at: timestamp
- invitee_id: string
- invitee_email: string
- scheduled_event_start_time: timestamp
- event_type: string
- utm_source: string
- utm_campaign: string
- raw_payload: struct (JSON)

Bronze data preserves source-system fidelity and is not mutated.

⬜ Silver Layer – Cleaned & Validated

- event_date: date **(Partition Column)**
- invitee_id: string **(Primary Key)**
- booking_date: date
- channel: string
- employee_email: string
- event_start_time: timestamp
- ingestion_date: date
- is_valid_record: boolean

Applied transformations:

- ✓ Type casting and schema enforcement
- ✓ Null handling and field standardization
- ✓ Deduplication using Primary key
- ✓ Data validation rules

🟧 Gold Layer – Analytics Ready

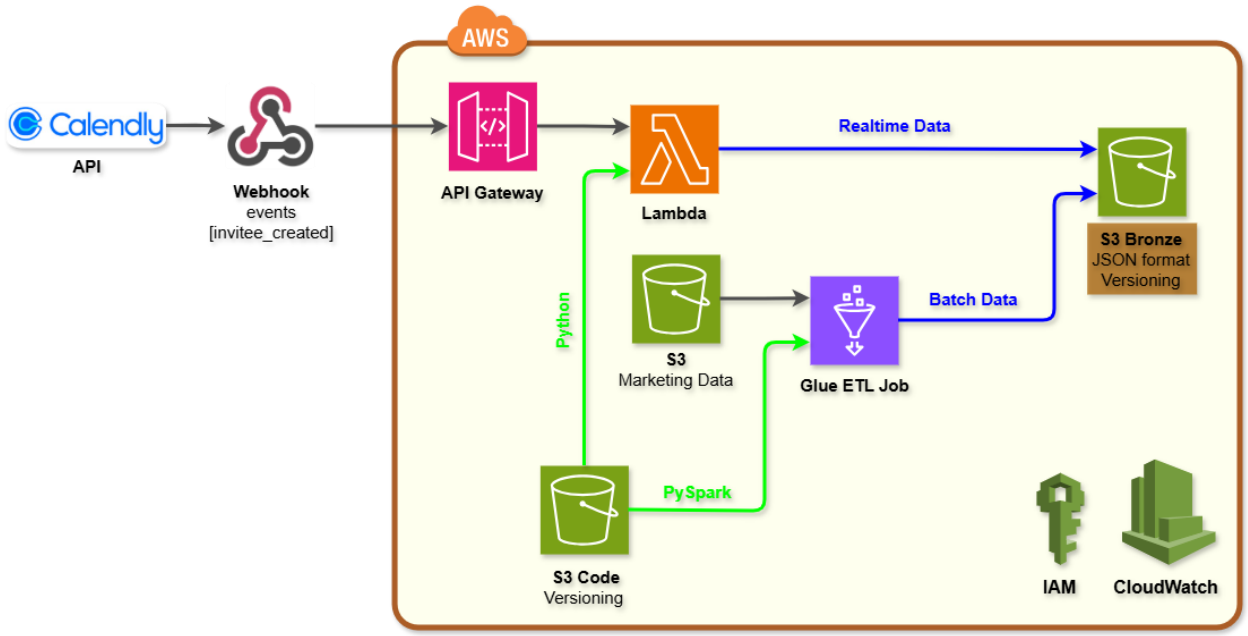
- booking_date: date **(Partition Column)**
- channel: string
- booking_hour: timestamp
- booking_week: int
- total_bookings: int
- total_spend: double
- cost_per_booking: double

Designed for BI tools, dashboards, and ad-hoc SQL queries.

Step 1 – Data Ingestion

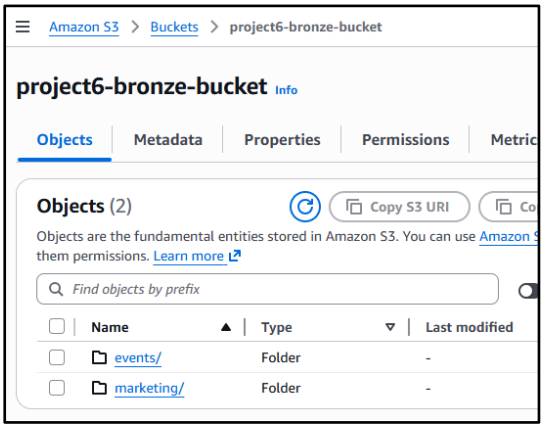
1-1- Objective

The objective of this step is to ingest raw invitee event files from Calenly API Webhook, in **realtime format**, and also daily marketing cost data from the DEA public S3 bucket, in the **batch format**, into an Amazon S3 bucket, named **project6-bronze-bucket**, in the JSON format. To comply with the project requirement that allows me to use Python, I will implement **AWS Lambda** for realtime data ingestion, via **AWS API Gateway**. Moreover, I used **AWS Glue ETL** job for batch data ingestion. This hybrid approach ensures that the ingestion process is both scalable and aligned with other AWS services in orchestration.



1-2- S3 Bronze Layer

I used Amazon S3 service and create a bucket with name of **s3://project6-bronze-bucket/**. After that, I created two folders inside that bucket with the name of **events/** folder (for ingestion of new raw invitee event files in realtime mode), and **marketing/** folder (for ingestion of daily marketing cost for last 30 days).

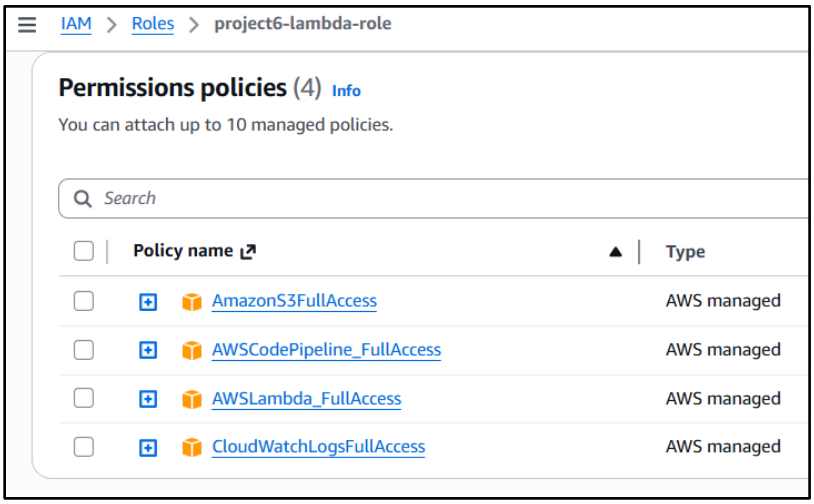


1-3- IAM Roles

Before starting data ingestion using Lambda, I configured an IAM role to enable Lambda to securely access the required AWS services during job execution. The IAM role was named **project6-lambda-role** and tagged with **project: 6**, and it was attached to the AWS Lambda functions to ensure secure and authorized access during execution.

The following permissions were configured:

- **AmazonS3FullAccess:** Granted to allow Lambda to write to the Bronze S3 bucket.
- **CloudCodePipeline_FullAccess:** Enabled triggering the CodePipeline during CI/CD.
- **AmazonLambda_FullAccess:** Granted to allow creation, execution, and management of Lambda functions involved in webhook ingestion and lead enrichment workflows.
- **CloudWatchLogsFullAccess:** Enabled logging and monitoring of Lambda function execution in Amazon CloudWatch.



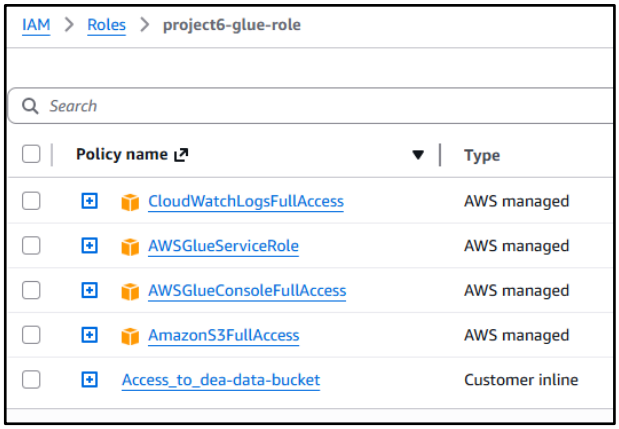
Also, I configured another IAM role to enable AWS Glue jobs to securely access the required AWS services during job execution. The IAM role was named **project6-glue-role** and tagged with **project: 6**, and it was attached to the AWS Glue ETL jobs to ensure secure and authorized access during execution.

The following permissions were configured:

- **AmazonS3FullAccess:** Granted to allow AWS Glue to read from and write to the Bronze, Silver, and Gold S3 buckets.
- **CloudWatchLogsFullAccess:** Enabled logging and monitoring of Glue job execution in Amazon CloudWatch.
- **AWSGlueConsoleFullAccess:** Attached to my IAM user to allow me to create and manage AWS Glue resources, such as ETL jobs, and workflows, through the AWS Management Console.
- **AWSGlueServiceRole:** Attached to the Glue job runtime role, allowing AWS Glue to assume the role at execution time and access required services, including Amazon S3, AWS Secrets Manager, and Amazon CloudWatch Logs resources.

- **Access_to_dea-data-bucket (inline)**: An inline policy added to the Glue job role to allow reading publicly available data from the DEA bucket. This policy permits s3:GetObject and s3:ListBucket actions on the dea-data-bucket and all its objects. Here is the policy:

```
{
        "Version": "2012-10-17",
        "Statement": [
                {
                        "Sid": "AllowReadPublicDEABucket",
                        "Effect": "Allow",
                        "Action": [
                                "s3:GetObject",
                                "s3:ListBucket"
                        ],
                        "Resource": [
                                "arn:aws:s3:::dea-data-bucket",
                                "arn:aws:s3:::dea-data-bucket/*"
                        ]
                }
        ]
}
```

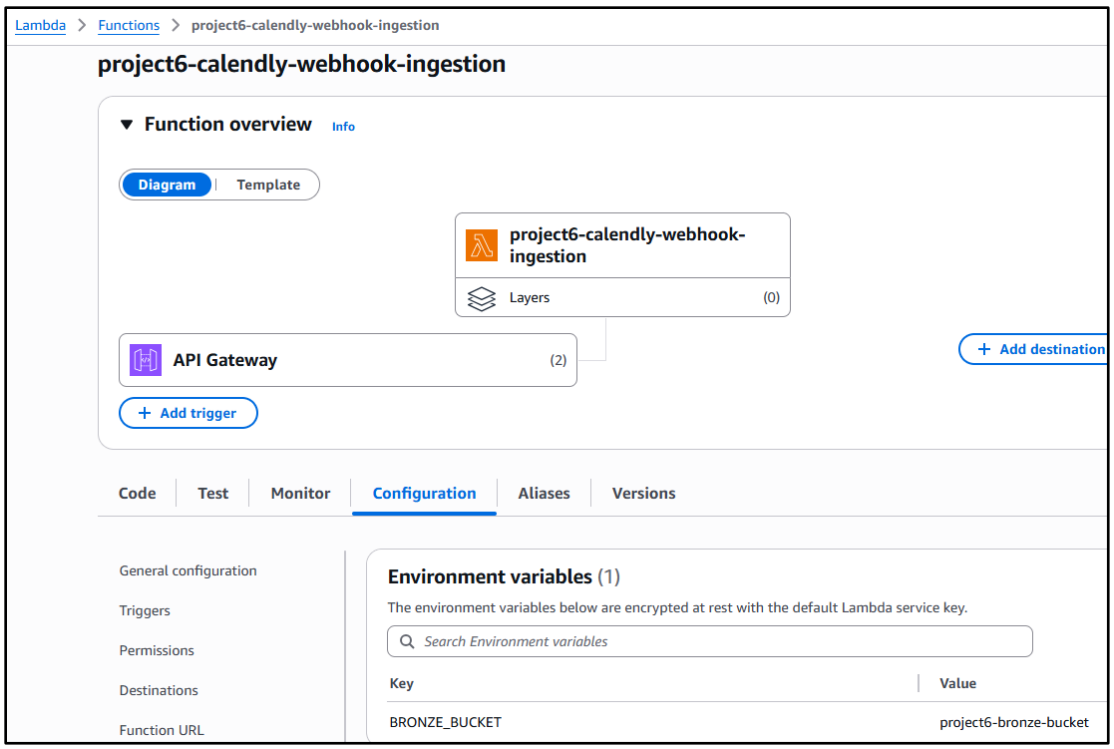


1-4- Lambda Function

I created the Lambda function, named **project6-calendly-webhook-ingestion**, to perform raw data ingestion from Calendly Webhook API into S3 Bronze bucket. The script file name in the Python language is **project6-calendly-webhook-ingestion.py**. I will use this function later in CI/CD section. I added one environment variable to this function as Bronze bucket name.

Key: BRONZE_BUCKET

Value: project6-bronze-bucket

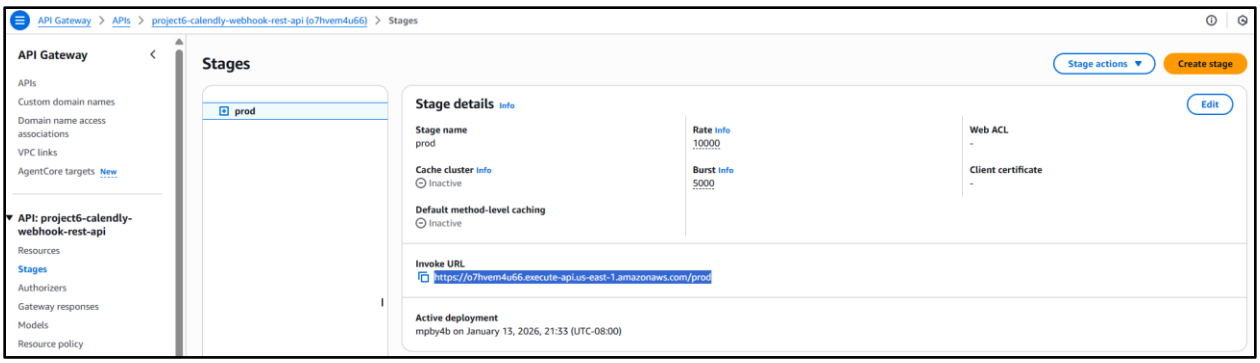


1-5- API Gateway

To get events from Calendly Webhook in the realtime format, I created an API Gateway, named **project6-calendly-webhook-rest-api**, to fetch data from Calendly Webhook. It will post events to my URL using REST API. After that, I created an URL stage in AWS using API Gateway.

After creating the API Gateway successfully, I got my URL address as below. I use this URL in Calendly Webhook configuration.

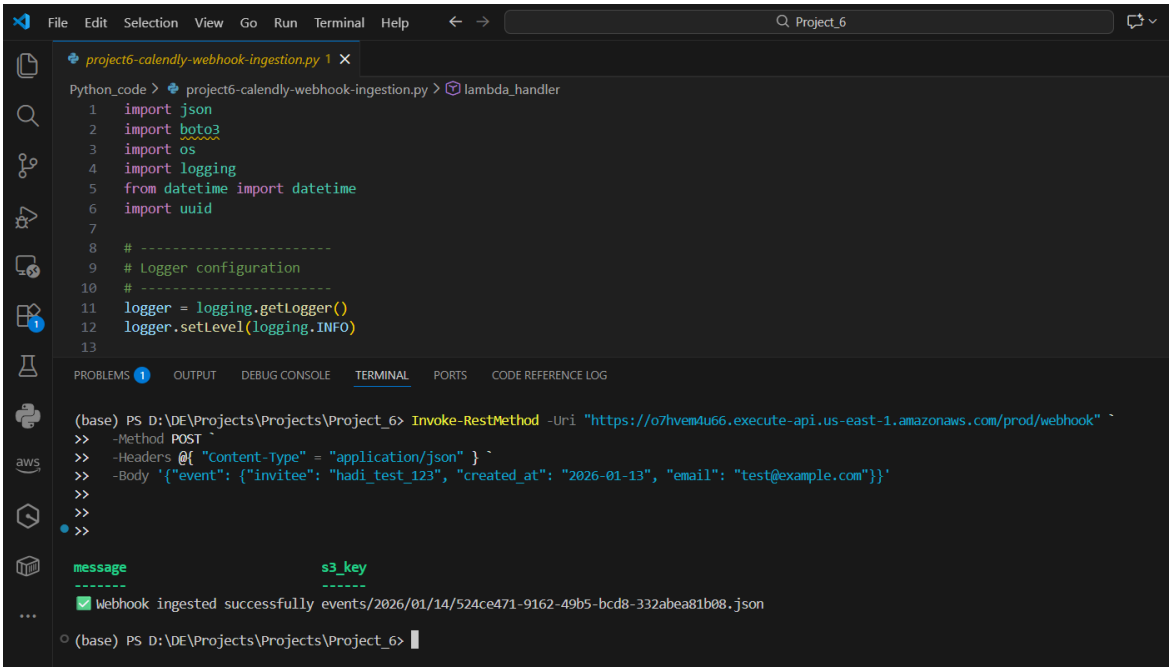
https://o7hvem4u66.execute-api.us-east-1.amazonaws.com/prod/webhook

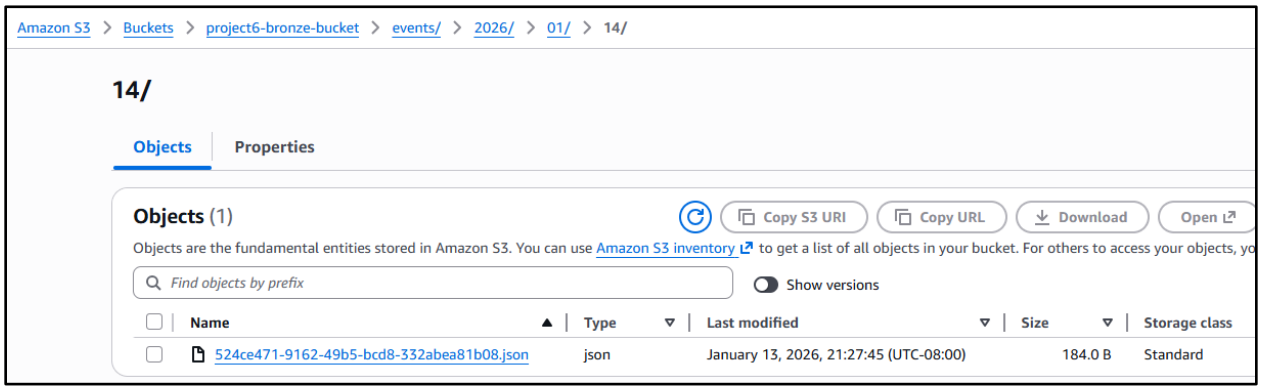


To test my API Gateway, I sent a fake event manually to my URL in VS Code terminal:

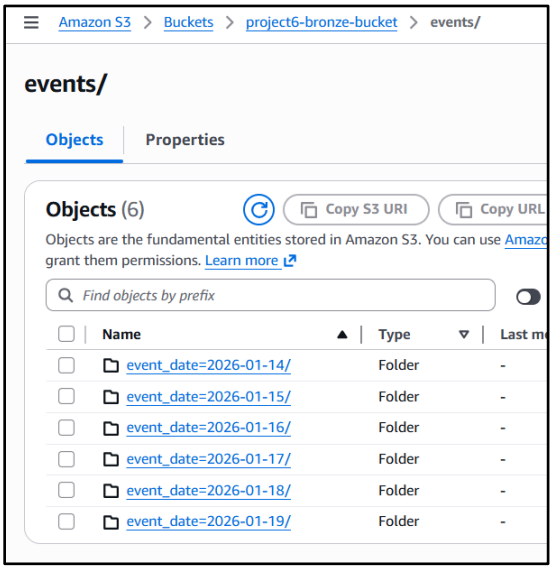
```
Invoke-RestMethod -Uri "https://o7hvem4u66.execute-api.us-east-1.amazonaws.com/prod/webhook" `
  -Method POST `
  -Headers @{ "Content-Type" = "application/json" } `
  -Body '{"event": {"invitee": "hadi_test_123", "created_at": "2026-01-13", "email": "test@example.com"}}'
```

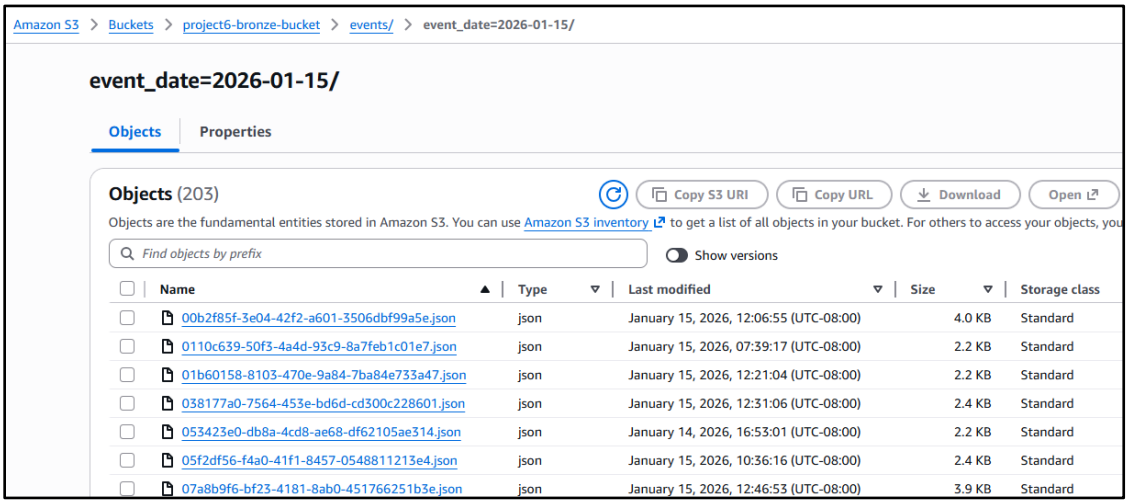
It works successfully!





Then, I request DEA manager to connect my URL to their available Calendly Webhook. After that I got several JSON files in my S3 bucket.

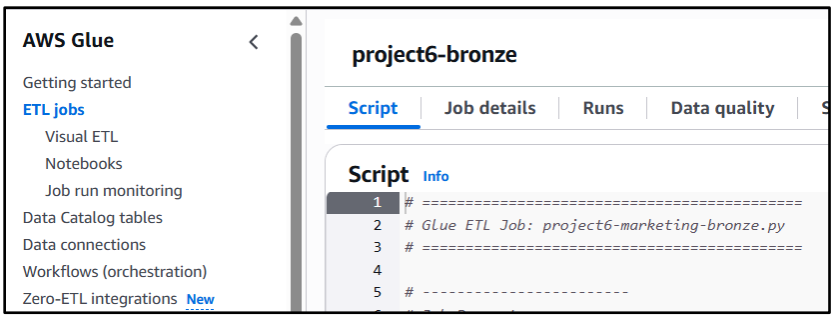


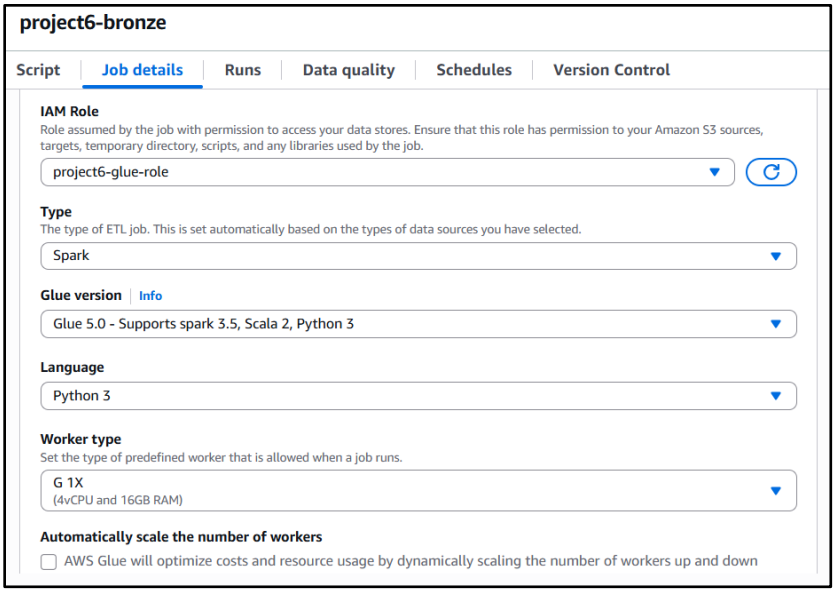


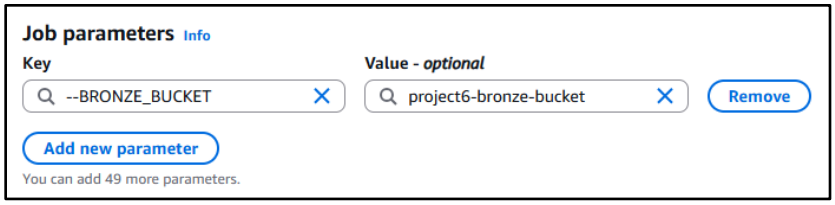
1-6- Glue ETL Job (S3-Bronze)

After establishing secure access between the DEA S3 bucket and my Bronze S3 bucket, I ingested the raw marketing data from the DEA S3 bucket into the Bronze layer using an **AWS Glue job** named **project6-bronze**. For testing purposes, the ETL logic was implemented as an inline PySpark script within the Glue job. In a production-level CI/CD setup, this script will be stored and managed in a dedicated S3 code repository. The PySpark script is named **project6-bronze.py**.

This Glue job is responsible for ingesting all files related to daily media cost data and storing them under **s3://project6-bronze-bucket/marketing/**. The job was configured with a single input parameter, defined in the **Job Parameters** section. To optimize resource usage during ingestion, minimal compute resources were selected, and the job execution timeout was set to **10 minutes**.

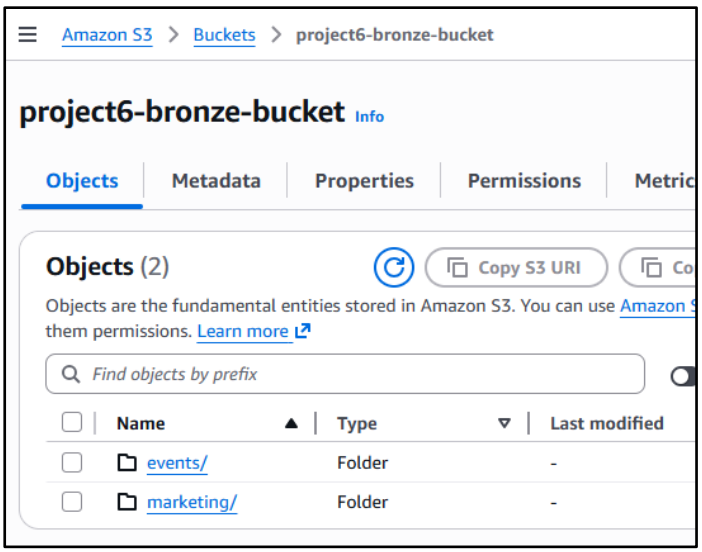






1-7- Demonestration

After setting up all above services, now I am going start the Bronze layer data ingestion. I asked Azmat to configure the Calendly Webhook setup to send events to my endpoint URL to get the realtime events. Also, in parallel, I ran the Glue function to ingest all marketing data for last 30 days from DEA public S3 bucket into my S3 Bronze bucket in the batch mode. My S3 bucket has structure like this:



This is structure of **event** files:

```
s3://project6-bronze-bucket/
└── events/
    ├── event_date=2026-01-14/       # 212 objects
    │   └── 008d3007-bec0-4abf-b074-dcb333e6e959.json
    │   └── …
    ├── event_date=2026-01-15/       # 266 objects
    │   └── 00b2f85f-3e04-42f2-a601-3506dbf99a5e.json
    │   └── …
    ├── event_date=2026-01-16/       # 292 objects
    │   └── 0112157c-3359-4b03-ac3e-1c3d65b81962.json
    │   └── …
    ├── event_date=2026-01-17/       # 175 objects
    │   └── 00132870-3a9a-480d-9d98-743a6188686b.json
    │   └── …
    ├── event_date=2026-01-18/       # 132 objects
    │   └── 02553eec-5cd8-4332-9b56-24717ca4ea24.json
    │   └── …
    ├── event_date=2026-01-19/       # 274 objects
    │   └── 0d6e6bd1-4397-4462-a43b-0a1c3276ecb4.json
    │   └── …
    ├── event_date=2026-01-20/       # 190 objects (so far)
    │   └── 02039453-9b50-44da-8a56-8d1016f543d5.json
```

To validate the silver layer data I downloaded them to my local machine and read with VS Code. This is the code for downloading the data using AWS CLI:

```
(base) PS D:\DE\Projects\Projects\Project_6> aws s3 cp s3://project6-bronze-bucket/events/
./data/Bronze/events/ --recursive --exclude "*" --include "*.json"
```

This is a sample of one of events, which the API Gateway fetch from Calendly Webhook:

0112157c-3359-4b03-ac3e-1c3d65b81962.json


```
{
  "ingestion_time": "2026-01-16T15:54:43.545190",
  "source": "calendly_webhook",
  "data": {
    "created_at": "2026-01-16T15:54:42.000000Z",
    "created_by": "https://api.calendly.com/users/8ec9d4df-39c5-463a-8b40-bcb5d0a70edf",
    "event": "invitee.created",
    "payload": {
      "cancel_url": "https://calendly.com/cancellations/64436c3b-b1a4-4840-b994-eb6eb69d2d3a",
      "created_at": "2026-01-16T15:54:41.302307Z",
      "email": "akinsjameson@gmail.com",
      "event": "https://api.calendly.com/scheduled_events/0a6874c5-b822-4db4-a46f-5cd90f1851d8",
      "first_name": null,
      "invitee_scheduled_by": "https://api.calendly.com/users/e43574f3-332f-4da5-9ce1-c10248f49ff5",
      "last_name": null,
      "name": "Akin Akinola ",
      "new_invitee": null,
      "no_show": null,
      "old_invitee": "https://api.calendly.com/scheduled_events/d3bfe89e-c98f-498f-92e1-024683233693/invitees/85968cbc-6180-4cf3-b33b-a25023db18f1",
      "payment": null,
      "questions_and_answers": [

      ],
      "reconfirmation": null,
      "reschedule_url": "https://calendly.com/reschedulings/64436c3b-b1a4-4840-b994-eb6eb69d2d3a",
      "rescheduled": false,
      "routing_form_submission": null,
      "scheduled_event": {
        "created_at": "2026-01-16T15:54:41.279214Z",
        "end_time": "2026-01-20T18:45:00.000000Z",
        "event_guests": [

        ],
        "event_memberships": [
          {
            "user": "https://api.calendly.com/users/e43574f3-332f-4da5-9ce1-c10248f49ff5",
            "user_email": "om@dataengineeracademy.com",
            "user_name": "Om Gaikhe"
          }
        ],
        "event_type": "https://api.calendly.com/event_types/4392759b-c2cf-49eb-bfba-42da9eec2a49",
        "invitees_counter": {
          "total": 1,
          "active": 1,
          "limit": 1
        },
        "location": {
          "join_url": "https://calendly.com/events/0a6874c5-b822-4db4-a46f-5cd90f1851d8/google_meet",
          "status": "processing",
          "type": "google_conference"
        },
        "meeting_notes_html": null,
        "meeting_notes_plain": null,
        "name": "VIP Onboarding",
        "start_time": "2026-01-20T18:15:00.000000Z",
        "status": "active",
        "updated_at": "2026-01-16T15:54:41.279214Z",
        "uri": "https://api.calendly.com/scheduled_events/0a6874c5-b822-4db4-a46f-5cd90f1851d8"
      },
      "scheduling_method": "instant_book",
      "status": "active",
      "text_reminder_number": null,
      "timezone": "America/New_York",
      "tracking": {
        "utm_campaign": null,
        "utm_source": null,
        "utm_medium": null,
        "utm_content": null,
        "utm_term": null,
        "salesforce_uuid": null
      },
      "updated_at": "2026-01-16T15:54:41.339370Z",
      "uri": "https://api.calendly.com/scheduled_events/0a6874c5-b822-4db4-a46f-5cd90f1851d8/invitees/64436c3b-b1a4-4840-b994-eb6eb69d2d3a"
    }
  }}
```

Also, this is the structure of **marketing** files:

```
s3://project6-bronze-bucket/
└── marketing/
    ├── file_index.json
    ├── spend_date=2025-12-16.json
    ├── spend_date=2025-12-17.json
    ├── ...
    ├── spend_date=2026-01-16.json
    ├── spend_date=2026-01-17.json
    ├── spend_date=2026-01-18.json
    └── spend_date=2026-01-19.json
```

To extract the above information, I used the data which are publicly available at DEA Public Database (only the data of last 30 days):

```
https://dea-data-bucket.s3.us-east-1.amazonaws.com/calendly_spend_data/file_index.json

https://dea-data-bucket.s3.us-east-1.amazonaws.com/calendly_spend_data/spend_data_2025-12-21.json
https://dea-data-bucket.s3.us-east-1.amazonaws.com/calendly_spend_data/spend_data_2025-12-22.json
...
https://dea-data-bucket.s3.us-east-1.amazonaws.com/calendly_spend_data/spend_data_2026-01-18.json
https://dea-data-bucket.s3.us-east-1.amazonaws.com/calendly_spend_data/spend_data_2026-01-19.json
```

Then, I used the first index file to read the file names and use it as per availability. The rest of files are as a sample for today (2026-01-20). After running the Glue job, I got these data in my S3 bronze bucket. I used this code for downloading the data using AWS CLI:

```
(base) PS D:\DE\Projects\Projects\Project_6> aws s3 cp s3://project6-bronze-bucket/marketing/
./data/Bronze/marketing/ --recursive --exclude "*" --include "*.json"
```

This is the data for the index file at the date of 2026-01-18 (only last month's data will be available daily):


```
{
  "files": [
    "spend_data_2025-12-21.json",
    "spend_data_2025-12-22.json",
    "spend_data_2025-12-23.json",
    "spend_data_2025-12-24.json",
    "spend_data_2025-12-25.json",
    "spend_data_2025-12-26.json",
    "spend_data_2025-12-27.json",
    "spend_data_2025-12-28.json",
    "spend_data_2025-12-29.json",
    "spend_data_2025-12-30.json",
    "spend_data_2025-12-31.json",
    "spend_data_2026-01-01.json",
    "spend_data_2026-01-02.json",
    "spend_data_2026-01-03.json",
    "spend_data_2026-01-04.json",
    "spend_data_2026-01-05.json",
    "spend_data_2026-01-06.json",
    "spend_data_2026-01-07.json",
    "spend_data_2026-01-08.json",
    "spend_data_2026-01-09.json",
    "spend_data_2026-01-10.json",
    "spend_data_2026-01-11.json",
    "spend_data_2026-01-12.json",
    "spend_data_2026-01-13.json",
    "spend_data_2026-01-14.json",
    "spend_data_2026-01-15.json",
    "spend_data_2026-01-16.json",
    "spend_data_2026-01-17.json",
    "spend_data_2026-01-18.json",
    "spend_data_2026-01-19.json"]}
```


Note: I got the information of `spend_date=2026-01-19.json`, yesterday 😉.

Also, this is sample data for daily marketing files, which the Glue ETL job fetches from DEA publick S3 database (the spend amount is in USD currency):

spend_data_2026-01-15.json


```
[
  {
    "date": "2026-01-15",
    "channel": "youtube_paid_ads",
    "spend": 381.76
  },
  {
    "date": "2026-01-15",
    "channel": "facebook_paid_ads",
    "spend": 473.8
  },
  {
    "date": "2026-01-15",
    "channel": "tiktok_paid_ads",
    "spend": 563.78
  }
]
```

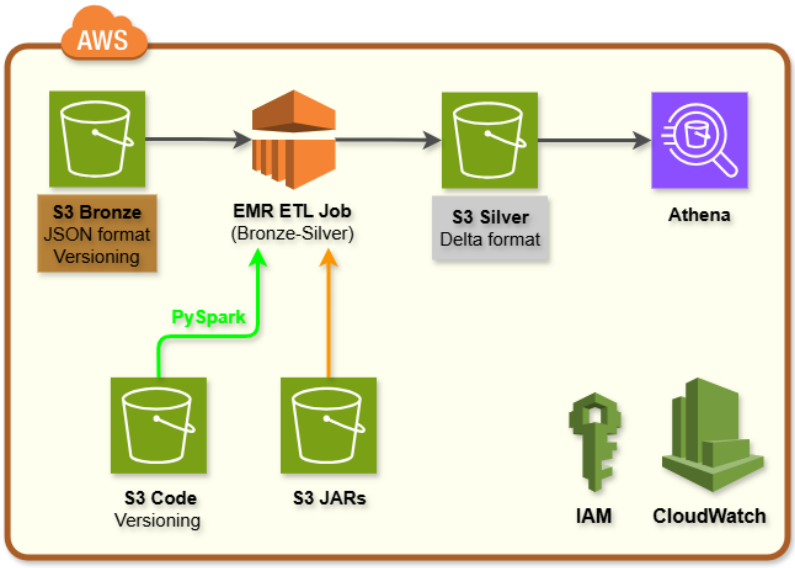

The Bronze layer data was then validated by downloading and manually reviewing the files, and all checks were successful.

Step 2 – Transformation (S3 Silver Layer)

2-1- Objective

The objective of the Silver layer is to transform raw ingested JSON files into clean, standardized, and analytically ready datasets. This layer focuses on enhancing data quality by removing duplicates, enforcing schemas, and preparing fact and dimension tables for downstream analytics and metric computation. Depending on data complexity and project requirements, the data in this layer is stored in Delta table format.

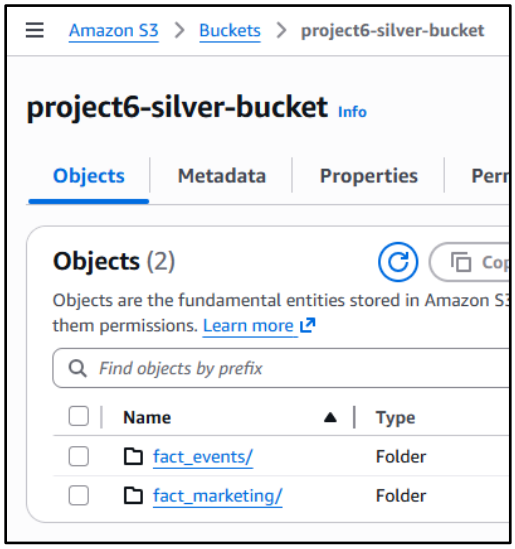
Unlike a previous project in which AWS Glue ETL jobs were used for data transformation, where the output was limited to Parquet format, this project leverages an **EMR Serverless ETL job** for the transformation step. EMR Serverless enables native support for writing **Delta tables**, making it a more suitable choice for implementing the Silver layer in this architecture.



2-2- S3 Silver Layer

I used the Amazon S3 service to create a bucket named **s3://project6-silver-bucket/**. All JSON files from the Bronze layer are first fully and deeply flattened, then transformed into structured datasets, and finally, after data cleansing, stored in Delta format within their respective folders in this layer. The Silver layer data is organized into fact-oriented datasets, enabling efficient joins and aggregations in subsequent processing stages. Two folders, **fact_events/** and **fact_marketings/**, were created in this bucket to store the corresponding fact tables. The structure of this bucket is as follows:

```
s3://project6-silver-bucket/
├── fact_events/
│   ├── _delta_log/
│   ├── event_date=2026-01-14/
│   ├── event_date=2026-01-15/
│   ├── event_date=2026-01-16/
│   │   ├── part-00001-4227ef1f-5cbe-4020-8b97-ad23aa1bc2e1.c000.snappy.parquet
│   │   ├── ...
│   │   └── part-00033-14ab10a9-262b-46d3-8ecc-434714f6d310.c000.snappy.parquet
│   ├── event_date=2026-01-17/
│   ├── event_date=2026-01-18/
│   ├── event_date=2026-01-19/
│   └── event_date=2026-01-20/
│
└── fact_marketing/
    ├── _delta_log/
    ├── date=2025-12-16/
    │   └── part-00000-cb48c0dd-3a5d-4bd5-8bc9-8de4b8070052.c000.snappy.parquet
    ├── date=2025-12-17/
    │   └── part-00000-e2b9ad1d-9ebe-467c-b2db-95bfce844fbe.c000.snappy.parquet
    │
    ├── date=2026-01-17/
    │   └── part-00002-f120bcef-8eaa-41da-bea8-4146bafd2dcc.c000.snappy.parquet
    ├── date=2026-01-18/
    │   └── part-00002-4a82d091-7873-4869-9ff2-0f06a351566a.c000.snappy.parquet
    └── date=2026-01-19/
        └── part-00002-9cdabd08-ed39-4182-94c8-1d5f942c5b2c.c000.snappy.parquet
```

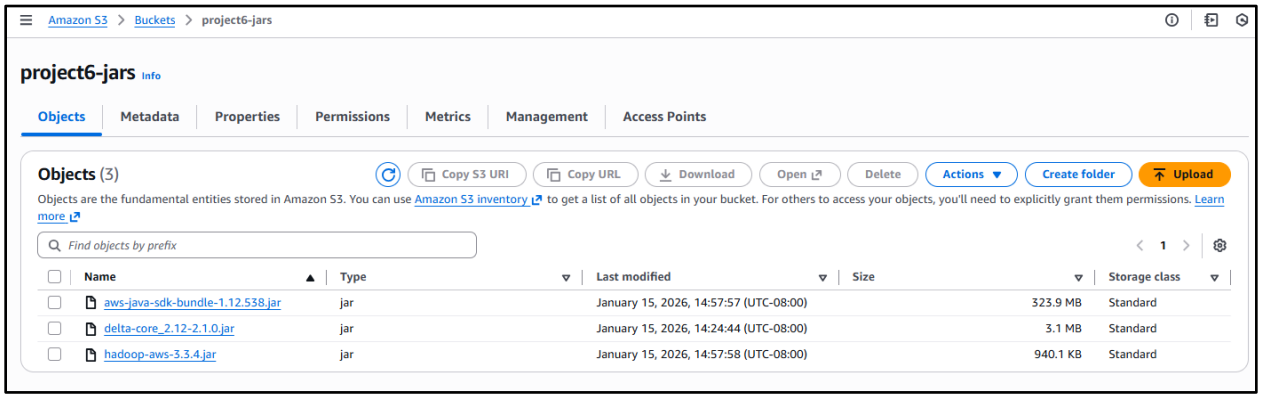


Additionally, **EMR Serverless** requires external dependencies to be explicitly provided during job configuration. To support this requirement, a dedicated S3 bucket named **s3://project6-jars/** was created to store all necessary **JAR dependencies**. These JAR files were downloaded from the **Maven Central repository** (https://mvnrepository.com/) and uploaded to this bucket. During EMR Serverless job configuration, the JARs location is explicitly referenced to ensure they are available at runtime.

The following JAR dependencies were attached:

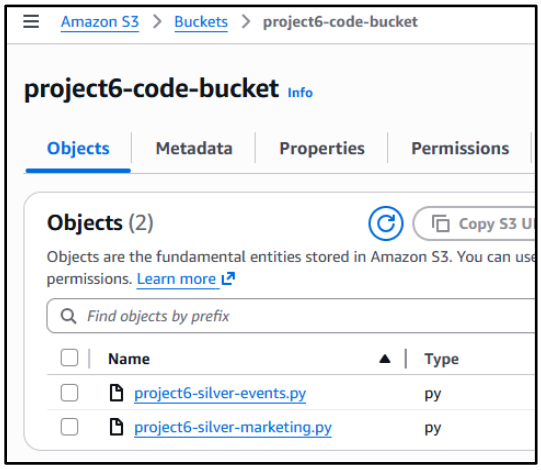
1. **Delta Lake support:** **delta-core_2.12-2.1.0.jar**
2. **Amazon S3 filesystem integration:** **hadoop-aws-3.3.4.jar**
3. **AWS SDK for Java:** **aws-java-sdk-bundle-1.12.538.jar**

This configuration enables EMR Serverless to reliably read from and write to Delta tables stored in Amazon S3 while maintaining transactional consistency and compatibility with AWS services.



Moreover, unlike AWS Lambda or AWS Glue jobs, which provide an inline editor for embedding transformation scripts, **EMR Serverless** does not offer a built-in interface for authoring or storing job code. Instead, EMR Serverless requires transformation scripts to be written externally in **PySpark** and **stored in an Amazon S3 location**, with the script path explicitly provided at job submission time. This approach aligns with best practices for CI/CD-oriented data pipelines.

To support this design, a dedicated S3 bucket was created to store all ETL scripts, named **s3://project6-code-bucket/**. In the production CI/CD workflow, this bucket will be populated automatically from a GitHub repository using AWS CodePipeline. For the Silver layer transformations, two PySpark scripts were developed and stored in this bucket: **project6-silver-events.py** and **project6-silver-marketing.py**. These scripts are responsible for transforming Bronze layer data into structured, Delta-formatted datasets in the Silver layer.



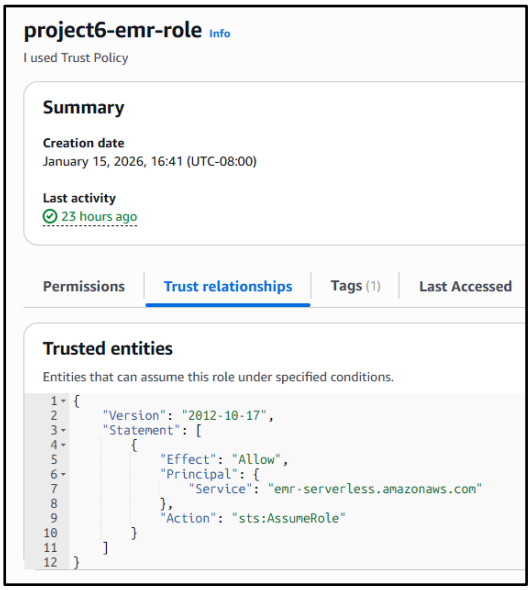
2-3- Partition Strategy for Silver Delta Lake Tables

To optimize query performance in the Silver layer, the Delta Lake tables are partitioned by `event_date`, which serves as a natural time-based **partition key**. Partitioning by date ensures that queries filtering on specific time periods, such as daily or weekly aggregates, can scan only the relevant partitions, significantly reducing I/O and improving processing speed. This strategy is particularly beneficial for time-series data, where queries are often centered around specific dates or date ranges. Additionally, **low-cardinality partitions** were chosen for `event_date`, as partitioning by high-cardinality fields (e.g., `invitee_id`) would result in an excessive number of partitions, leading to performance degradation. By selecting `event_date` as the partition key, we strike a balance between efficient data retrieval and manageable partition sizes, optimizing both storage and query performance for downstream analytics.

2-4- IAM Role

Before initiating data transformations using **EMR Serverless**, an IAM execution role was configured to allow EMR to securely access the required AWS services during job execution. This role, named **project6-emr-role**, was tagged with **project: 6** and assigned as the execution role for EMR Serverless applications to ensure secure and authorized access at runtime. I considered the IAM trust relationship as below:

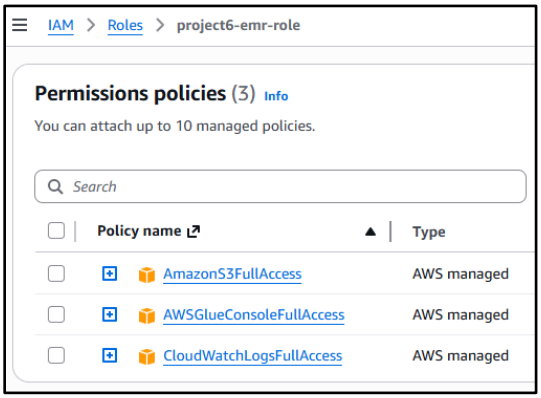
```
{
    "Version": "2012-10-17",
    "Statement": [
        {
            "Effect": "Allow",
            "Principal": {
                "Service": "emr-serverless.amazonaws.com"
            },
            "Action": "sts:AssumeRole"
        }
    ]
}
```



Then the following permissions were configured for this role:

- **AmazonS3FullAccess:** Granted to allow EMR Serverless jobs to read from and write to the Bronze, Silver, and Gold S3 buckets.
- **CloudWatchLogsFullAccess:** Enabled centralized logging and monitoring of EMR Serverless job executions in Amazon CloudWatch.
- **AWS Glue permissions:** Provided access to the AWS Glue Data Catalog, enabling EMR Serverless to read table metadata and schemas required for Delta Lake-based transformations.

This IAM configuration ensures secure, least-friction access to all required services while maintaining clear separation between orchestration, execution, and data access responsibilities.



2-5- EMR Job (Bronze - Silver)

In this project, the transformation layer was migrated from **AWS Glue ETL jobs** to **EMR Serverless jobs** to better support advanced data processing requirements. While AWS Glue provides a fully managed and serverless solution for data transformations, its native output formats are limited to Parquet and do not provide full support for Delta Lake transactional features. In contrast, EMR Serverless offers greater flexibility and native compatibility with Delta Lake, enabling ACID-compliant writes, efficient handling of incremental data, and improved support for schema evolution and partitioned fact tables. This transition allows the Silver layer to leverage Delta table capabilities more effectively, resulting in improved data reliability, scalability, and suitability for downstream analytics.

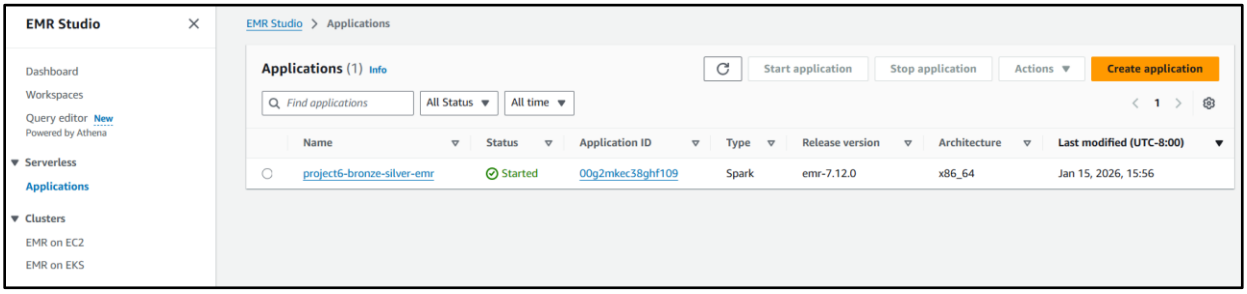
Amazon EMR provides two primary deployment models: **EMR on EC2** and **EMR Serverless**. EMR on EC2 requires provisioning and managing clusters composed of EC2 instances, offering fine-grained control over infrastructure but introducing additional operational overhead related to scaling, maintenance, and cost optimization. In contrast, EMR Serverless abstracts cluster management entirely, automatically provisioning and scaling compute resources based on workload demand. In this project, EMR Serverless was selected to perform data transformations because it eliminates infrastructure management, reduces operational complexity, and enables cost-efficient execution for intermittent batch workloads. This serverless approach aligns well with the project's daily transformation requirements while still providing the flexibility and performance needed to process Delta Lake tables effectively.

Then I started to create an EMR Serverless ETL job for transformation of data from S3 Bronze bucket to S3 Silver bucket. In AWS console, I clicked on the **EMR Serverless**, then clicked on **Create application (or manage the available applications)**.

After that I will pass to another page, named **EMR Studio**! In this page, I am trying to create an EMR Serverless application. I filled in the application form as below:

- **Name:** project6-bronze-silver-emr
- **Type:** Spark
- **Spark version:** 7.12.0 (matches Glue 4.0 and Delta JAR)
- **Execution role:** IAM role (**project6-emr-role**)
- **Tag:** project: 6

I selected the **Use default settings for batch jobs only** icon and left other defaults and cliked **Create**. Then, I got an **Application ID**, which I will use to submit jobs.



To submit the EMR ETL job, I downloaded 4 necessary **JAR dependencies** from the **Maven Central repository** (https://mvnrepository.com/) and uploaded to the JAR bucket **s3://project6-jars/**. The following JAR dependencies were attached:

1. **Delta Lake support:** delta-core_2.12-2.1.0.jar
2. **Amazon S3 filesystem integration:** hadoop-aws-3.3.4.jar
3. **AWS SDK for Java:** aws-java-sdk-bundle-1.12.538.jar

Also, I created two PySpark functions and put inside the code bucket **s3://project6-code-bucket** for transformation of Bronze layer data into Silver layer. I named them: **project6-silver-events.py** and **project6-silver-marketing.py**.

2-6- EMR ETL Jobs Submitting

Now, the EMR is ready to job sumitting. This job submitting will be done using VS Code powershell. To sumbit the job I need this information:

Parameters	Values	
Application-id	00g2mkec38ghf109	
Execution-role-arn	arn:aws:iam::000185048470:role/project6-emr-role	
EntryPoint	s3://project6-code-bucket/project6-silver-events.py s3://project6-code-bucket/project6-silver-marketing.py	
EntryPointArguments	["project6-bronze-bucket", "events/", "project6-silver-bucket"] ["project6-bronze-bucket", "marketing/", "project6-silver-bucket"]	
sparkSubmitParameters	**--jars**	s3://project6-jars/delta-core_2.12-2.1.0.jar, s3://project6-jars/hadoop-aws-3.3.4.jar, s3://project6-jars/aws-java-sdk-bundle-1.12.538.jar
	--conf	spark.sql.extensions=io.delta.sql.DeltaSparkSessionExtension
	--conf	spark.sql.catalog.spark_catalog=org.apache.spark.sql.delta.catalog.DeltaCatalog
	--conf	spark.sql.sources.partitionOverwriteMode=dynamic
	--conf	spark.delta.logStore.class=org.apache.spark.sql.delta.storage.S3SingleDriverLogStore

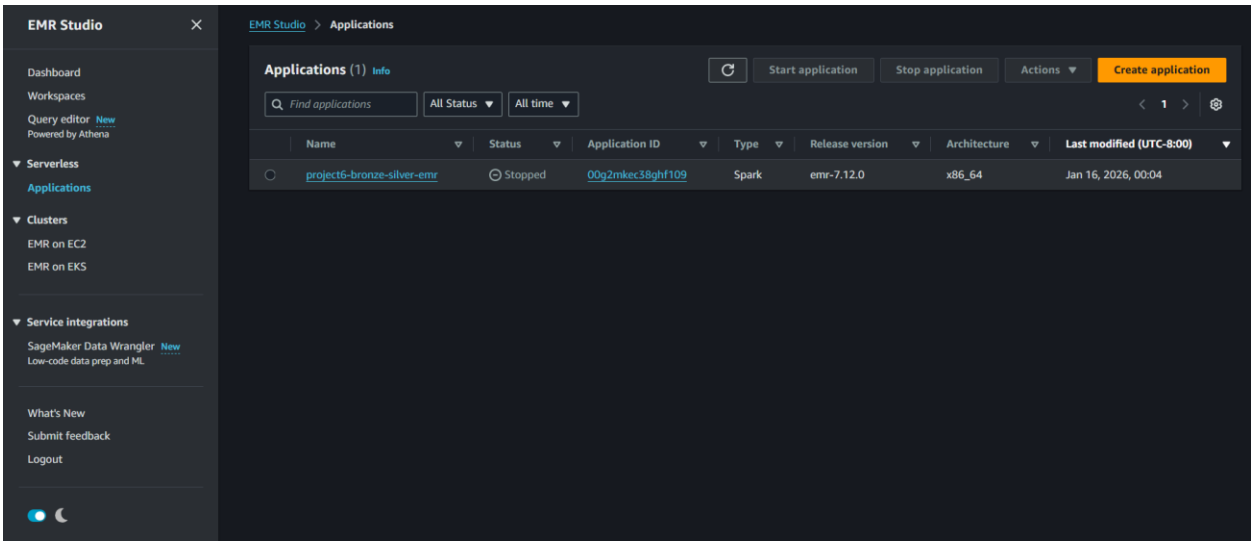
I used these two formats to submit two different jobs to EMR ETL separately for events and marketing data transformation:

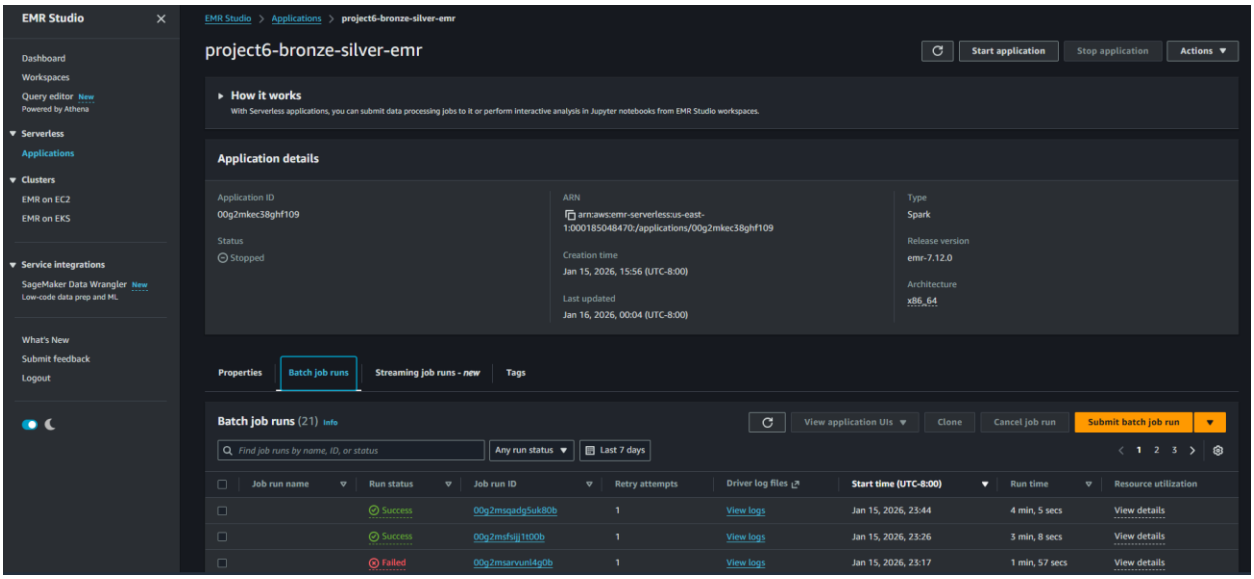
```
aws emr-serverless start-job-run `
  --application-id 00g2mkec38ghf109 `
  --execution-role-arn arn:aws:iam::000185048470:role/project6-emr-role `
  --job-driver "{
    `"sparkSubmit`": {
      `"entryPoint`": `"s3://project6-code-bucket/project6-silver-events.py`",
      `"entryPointArguments`": [`"project6-bronze-bucket`", `"events/`", `"project6-silver-bucket`"],
      `"sparkSubmitParameters`": `"--jars s3://project6-jars/delta-core_2.12-2.1.0.jar,s3://project6-
                                  jars/hadoop-aws-3.3.4.jar,s3://project6-jars/aws-java-sdk-bundle-
                                  1.12.538.jar --conf
                                  spark.sql.extensions=io.delta.sql.DeltaSparkSessionExtension --conf
                                  spark.sql.catalog.spark_catalog=org.apache.spark.sql.delta.catalog.DeltaC
                                  atalog --conf spark.sql.sources.partitionOverwriteMode=dynamic --conf
                                  spark.delta.logStore.class=org.apache.spark.sql.delta.storage.S3SingleDri
                                  verLogStore`"
    }
  }"
```

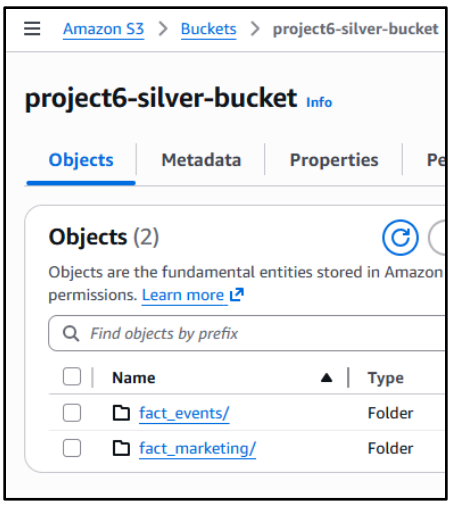
```
aws emr-serverless start-job-run `
  --application-id 00g2mkec38ghf109 `
  --execution-role-arn arn:aws:iam::000185048470:role/project6-emr-role `
  --job-driver "{
    `"sparkSubmit`": {
      `"entryPoint`": `"s3://project6-code-bucket/project6-silver-marketing.py`",
      `"entryPointArguments`": [`"project6-bronze-bucket`", `"marketing/`", `"project6-silver-bucket`"],
      `"sparkSubmitParameters`": `"--jars s3://project6-jars/delta-core_2.12-2.1.0.jar,s3://project6-
                                  jars/hadoop-aws-3.3.4.jar,s3://project6-jars/aws-java-sdk-bundle-
                                  1.12.538.jar --conf
                                  spark.sql.extensions=io.delta.sql.DeltaSparkSessionExtension --conf
                                  spark.sql.catalog.spark_catalog=org.apache.spark.sql.delta.catalog.DeltaC
                                  atalog --conf spark.sql.sources.partitionOverwriteMode=dynamic --conf
                                  spark.delta.logStore.class=org.apache.spark.sql.delta.storage.S3SingleDri
                                  verLogStore`"
    }
  }"
```

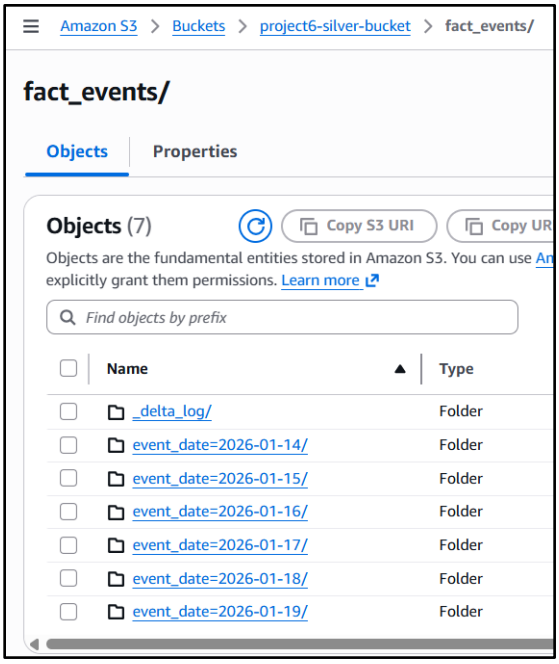
```
(p311) PS D:\DE\Projects\Projects\Project_6> aws emr-serverless start-job-run `
>>   --application-id 00g2mkec38ghf109 `
>>   --execution-role-arn arn:aws:iam::000185048470:role/project6-emr-role `
>>   --job-driver '{
>>         "sparkSubmit": {
>>             "entryPoint": "s3://project6-code-bucket/project6-bronze-silver.py",
>>             "entryPointArguments": ["project6-bronze-bucket", "marketing/", "project6-silver-bucket"],
>>             "sparkSubmitParameters": "--jars s3://project6-jars/delta-core_2.12-2.1.0.jar,s3://project6-jars/hadoop-aws-3.3.4.jar,s3://project6-jars/aws-java
-sdk-bundle-1.12.538.jar --conf spark.sql.extensions=io.delta.sql.DeltaSparkSessionExtension --conf spark.sql.catalog.spark_catalog=org.apache.spark.sql.delta.c
atalog.DeltaCatalog --conf spark.sql.sources.partitionOverwriteMode=dynamic --conf spark.delta.logStore.class=org.apache.spark.sql.delta.storage.S3SingleDriverL
ogStore"
>>         }
>>   }'
>>
{
    "applicationId": "00g2mkec38ghf109",
    "jobRunId": "00g2ml8p8bgkb80b",
    "arn": "arn:aws:emr-serverless:us-east-1:000185048470:/applications/00g2mkec38ghf109/jobruns/00g2ml8p8bgkb80b"
}
(p311) PS D:\DE\Projects\Projects\Project_6>
```

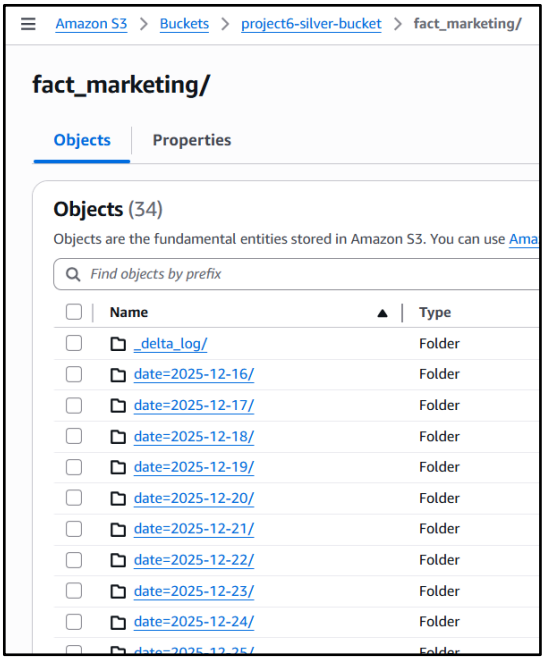
After submitting the EMR Jobs, and getting the successful running, I found that two fact tables are created in the Silver layer.











There are two folders inside each of them:

- **_delta_log/** folder
- **Parquet** files for partitions (**event_date=.../** or **date=.../**)

2-7- Silver Layer Data Validation Using AWS CLI

To validate the data in the Silver layer, all **Parquet** files (stored as Delta tables) were downloaded from the Silver S3 bucket to the local machine. The following AWS CLI commands were used to recursively copy only the Parquet files for each dataset:

fact_events/

```
aws s3 cp s3://project6-silver-bucket/fact_events/ ./data/Silver/fact_events/ --recursive --exclude "*" --include "*.parquet"
```

fact_marketing/

```
aws s3 cp s3://project6-silver-bucket/fact_marketing/ ./data/Silver/fact_marketing/ --recursive --exclude "*" --include "*.parquet"
```

After downloading the Parquet files, the datasets were explored in a Jupyter Notebook using the Pandas library. The Parquet files were loaded into Pandas DataFrames and carefully reviewed to validate schema consistency, data integrity, and transformation correctness. The validation confirmed that the Silver layer data was successfully processed and met the expected quality standards. Screenshots of two representative DataFrames are provided below.

fact_events

```
# List all Parquet files in folder
files = glob.glob("../data/Silver/fact_events/*/*.parquet")
# display(files)

# Read and concatenate them
df_fact_events = pd.concat([pd.read_parquet(f, engine="fastparquet") for f in files], ignore_index=True)
display(df_fact_events.tail())
df_fact_events.info()
```

[4] ✓ 0.6s Python

	ingestion_time	source	data_created_at	data_created_by	data_event	data_payload_cancel_url	data_payload_created_at	data_pa
3619	2026-01-16T04:31:18.238616	calendly_webhook	2026-01-16T04:31:18.000000Z	https://api.calendly.com/users/8ec9d4df-39c5-4...	invitee.created	https://calendly.com/cancellations/b9863f0b-6e...	2026-01-16T04:31:17.359022Z	hodgson.doug.a
3620	2026-01-16T00:51:31.376298	calendly_webhook	2026-01-16T00:51:31.000000Z	https://api.calendly.com/users/8ec9d4df-39c5-4...	invitee.created	https://calendly.com/cancellations/73230f38-25...	2026-01-16T00:51:30.322986Z	
3621	2026-01-16T04:56:41.102266	calendly_webhook	2026-01-16T04:56:40.000000Z	https://api.calendly.com/users/8ec9d4df-39c5-4...	invitee.created	https://calendly.com/cancellations/ef9c8d67-fa...	2026-01-16T04:56:38.113459Z	ausbai0926
3622	2026-01-16T00:14:41.686066	calendly_webhook	2026-01-16T00:14:40.000000Z	https://api.calendly.com/users/8ec9d4df-39c5-4...	invitee.created	https://calendly.com/cancellations/2535600c-ed...	2026-01-16T00:14:40.005851Z	emao0705
3623	2026-01-16T00:18:26.390953	calendly_webhook	2026-01-16T00:18:25.000000Z	https://api.calendly.com/users/8ec9d4df-39c5-4...	invitee.created	https://calendly.com/cancellations/808b395c-5d...	2026-01-16T00:18:24.702123Z	rtoke11

5 rows × 68 columns

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 9621 entries, 0 to 9620
Data columns (total 68 columns):
 #   Column                                  Non-Null Count  Dtype
---  ------                                  --------------  -----
 0   ingestion_time                          3624 non-null   object
 1   source                                  3624 non-null   object
 2   data_created_at                         3624 non-null   object
 3   data_created_by                         3624 non-null   object
 4   data_event                              3624 non-null   object
 5   data_payload_cancel_url                 3624 non-null   object
 6   data_payload_created_at                 3624 non-null   object
 7   data_payload_email                      3624 non-null   object
 8   data_payload_event                      3624 non-null   object
 9   data_payload_first_name                 0 non-null      object
 10  data_payload_invitee_scheduled_by       2005 non-null   object
 11  data_payload_last_name                  0 non-null      object
 12  data_payload_name                       3624 non-null   object
 13  data_payload_new_invitee                0 non-null      object
 14  data_payload_no_show                    0 non-null      object
 15  data_payload_old_invitee                695 non-null    object
 16  data_payload_payment                    0 non-null      object
 17  data_payload_reschedule_url             3624 non-null   object
 18  data_payload_rescheduled                3624 non-null   bool
 19  data_payload_routing_form_submission    23 non-null     object
 20  data_payload_scheduling_method          701 non-null    object
 21  data_payload_status                     3624 non-null   object
 22  data_payload_text_reminder_number       2443 non-null   object
 23  data_payload_timezone                   3624 non-null   object
 24  data_payload_updated_at                 3624 non-null   object
 25  data_payload_uri                        3624 non-null   object
 26  data_payload_reconfirmation_confirmed_at  0 non-null    object
 27  data_payload_reconfirmation_created_at  1 non-null      object
```

```
 28  data_payload_scheduled_event_created_at                                  3624 non-null   object
 29  data_payload_scheduled_event_end_time                                    3624 non-null   object
 30  data_payload_scheduled_event_event_type                                  3624 non-null   object
 31  data_payload_scheduled_event_meeting_notes_html                          0 non-null      object
 32  data_payload_scheduled_event_meeting_notes_plain                         0 non-null      object
 33  data_payload_scheduled_event_name                                        3624 non-null   object
 34  data_payload_scheduled_event_start_time                                  3624 non-null   object
 35  data_payload_scheduled_event_status                                      3624 non-null   object
 36  data_payload_scheduled_event_updated_at                                  3624 non-null   object
 37  data_payload_scheduled_event_uri                                         3624 non-null   object
 38  data_payload_tracking_salesforce_uuid                                    0 non-null      object
 39  data_payload_tracking_utm_campaign                                       22 non-null     object
 40  data_payload_tracking_utm_content                                        22 non-null     object
 41  data_payload_tracking_utm_medium                                         17 non-null     object
 42  data_payload_tracking_utm_source                                         1 non-null      object
 43  data_payload_tracking_utm_term                                           22 non-null     object
 44  data_payload_questions_and_answers_answer                                3341 non-null   object
 45  data_payload_questions_and_answers_position                              3341 non-null   float64
 46  data_payload_questions_and_answers_question                              3341 non-null   object
 47  data_payload_scheduled_event_invitees_counter_active                     3624 non-null   int64
 48  data_payload_scheduled_event_invitees_counter_limit                      3624 non-null   int64
 49  data_payload_scheduled_event_invitees_counter_total                      3624 non-null   int64
 50  data_payload_scheduled_event_location_join_url                           3380 non-null   object
 51  data_payload_scheduled_event_location_location                           50 non-null     object
 52  data_payload_scheduled_event_location_status                             3380 non-null   object
 53  data_payload_scheduled_event_location_type                               3624 non-null   object
 54  data_payload_scheduled_event_event_guests_created_at                     1 non-null      object
 55  data_payload_scheduled_event_event_guests_email                          1 non-null      object
 56  data_payload_scheduled_event_event_guests_updated_at                     1 non-null      object
 57  data_payload_scheduled_event_event_memberships_user                      3624 non-null   object
 58  data_payload_scheduled_event_event_memberships_user_email                3624 non-null   object
 59  data_payload_scheduled_event_event_memberships_user_name                 3624 non-null   object
 60  data_payload_scheduled_event_location_data_id                            3260 non-null   float64
 61  data_payload_scheduled_event_location_data_password                      3260 non-null   object
 62  data_payload_scheduled_event_location_data_extra_intl_numbers_url        0 non-null      object
 63  data_payload_scheduled_event_location_data_settings_global_dial_in_numbers_city          1146 non-null   object
 64  data_payload_scheduled_event_location_data_settings_global_dial_in_numbers_country       3247 non-null   object
 65  data_payload_scheduled_event_location_data_settings_global_dial_in_numbers_country_name  3247 non-null   object
 66  data_payload_scheduled_event_location_data_settings_global_dial_in_numbers_number        3247 non-null   object
 67  data_payload_scheduled_event_location_data_settings_global_dial_in_numbers_type          3247 non-null   object
dtypes: bool(1), float64(2), int64(3), object(62)
memory usage: 1.9+ MB
```

As you can see, there are **68 nested values** in the **fact_events** data.

Next, I filter the **Facebook** events and find that there are **210 events** related to this channel.

Facebook

```
df_fact_events[df_fact_events['data_payload_scheduled_event_event_type'] == 'https://api.calendly.com/event_types/d639ecd3-8718-4068-955a-436b10d72c78']
```

0.0s Python

	ingestion_time	source	data_created_at	data_created_by	data_event	data_payload_cancel_url	data_payload_created_at	data_payload_email	
1629	2026-01-14T16:40:57.927701	calendly_webhook	2026-01-14T16:40:57.000000Z	https://api.calendly.com/users/8ec9d4df-39c5-4...	invitee.created	https://calendly.com/cancellations/c0dac920-4f...	2026-01-14T16:40:56.536746Z	srameshrn@gmail.com	https://api.calendly.com/sch
1684	2026-01-14T17:04:59.001449	calendly_webhook	2026-01-14T17:04:58.000000Z	https://api.calendly.com/users/8ec9d4df-39c5-4...	invitee.created	https://calendly.com/cancellations/4b210ca1-54...	2026-01-14T17:04:55.535946Z	abhilashreddykonda12@gmail.com	https://api.calendly.com/sch
1685	2026-01-14T23:43:08.481918	calendly_webhook	2026-01-14T23:43:08.000000Z	https://api.calendly.com/users/8ec9d4df-39c5-4...	invitee.created	https://calendly.com/cancellations/e4500662-b4...	2026-01-14T23:43:07.314544Z	biswasamalendu@gmail.com	https://api.calendly.com/sch
1686	2026-01-14T16:33:11.155932	calendly_webhook	2026-01-14T16:33:10.000000Z	https://api.calendly.com/users/8ec9d4df-39c5-4...	invitee.created	https://calendly.com/cancellations/3891a3de-b9...	2026-01-14T16:33:08.442961Z	christiankaby@hotmail.com	https://api.calendly.com/sch
1687	2026-01-14T19:01:02.363233	calendly_webhook	2026-01-14T19:01:02.000000Z	https://api.calendly.com/users/8ec9d4df-39c5-4...	invitee.created	https://calendly.com/cancellations/0f00c474-a6...	2026-01-14T19:01:00.959698Z	bkeymist@gmail.com	https://api.calendly.com/sch
...	...	...	...	...	...	...	...	...	
9605	2026-01-20T02:08:24.511476	calendly_webhook	2026-01-20T02:08:24.000000Z	https://api.calendly.com/users/8ec9d4df-39c5-4...	invitee.created	https://calendly.com/cancellations/30c34ef4-5c...	2026-01-20T02:08:23.315557Z	boomvicrox@gmail.com	https://api.calendly.com/sch
9606	2026-01-20T00:30:57.415345	calendly_webhook	2026-01-20T00:30:56.000000Z	https://api.calendly.com/users/8ec9d4df-39c5-4...	invitee.created	https://calendly.com/cancellations/33af4a25-b4...	2026-01-20T00:30:55.643373Z	gbolahandolani@gmail.com	https://api.calendly.com/sch
9611	2026-01-20T06:47:32.428321	calendly_webhook	2026-01-20T06:47:32.000000Z	https://api.calendly.com/users/8ec9d4df-39c5-4...	invitee.created	https://calendly.com/cancellations/b1c4f2f2-2f...	2026-01-20T06:47:31.364528Z	tonydegreat1@gmail.com	https://api.calendly.com/sch
9614	2026-01-20T02:37:49.235179	calendly_webhook	2026-01-20T02:37:48.000000Z	https://api.calendly.com/users/8ec9d4df-39c5-4...	invitee.created	https://calendly.com/cancellations/6b7adcc4-c2...	2026-01-20T02:37:47.483393Z	kriviears@gmail.com	https://api.calendly.com/sch
9618	2026-01-20T05:30:40.200711	calendly_webhook	2026-01-20T05:30:39.000000Z	https://api.calendly.com/users/8ec9d4df-39c5-4...	invitee.created	https://calendly.com/cancellations/5189c6b4-f3...	2026-01-20T05:30:38.470285Z	ghost@alphabetas.com	https://api.calendly.com/sch

283 rows × 68 columns

Next, I filter the **YouTube** events and find that there are **6 events** related to this channel.

YouTube

```
df_fact_events[df_fact_events['data_payload_scheduled_event_event_type'] == 'https://api.calendly.com/event_types/dbb4ec50-38cd-4bcd-bbff-efb7b5a6f098']
```

0.0s Python

	ingestion_time	source	data_created_at	data_created_by	data_event	data_payload_cancel_url	data_payload_created_at	data_payload_email	data_p
1693	2026-01-14T21:15:11.112336	calendly_webhook	2026-01-14T21:15:10.000000Z	https://api.calendly.com/users/8ec9d4df-39c5-4...	invitee.created	https://calendly.com/cancellations/ff100630-34...	2026-01-14T21:15:09.599437Z	csg2243@gmail.com	https://api.calendly.com/scheduled
3320	2026-01-15T00:26:39.585598	calendly_webhook	2026-01-15T00:26:39.000000Z	https://api.calendly.com/users/8ec9d4df-39c5-4...	invitee.created	https://calendly.com/cancellations/c38ec406-2c...	2026-01-15T00:26:38.443718Z	eledweezy@gmail.com	https://api.calendly.com/scheduled
5882	2026-01-17T15:36:07.869818	calendly_webhook	2026-01-17T15:36:07.000000Z	https://api.calendly.com/users/8ec9d4df-39c5-4...	invitee.created	https://calendly.com/cancellations/539b1ae0-83...	2026-01-17T15:36:06.389923Z	bruce_hofman@yahoo.com	https://api.calendly.com/scheduled
6464	2026-01-18T18:11:06.250220	calendly_webhook	2026-01-18T18:11:06.000000Z	https://api.calendly.com/users/8ec9d4df-39c5-4...	invitee.created	https://calendly.com/cancellations/8447f529-c2...	2026-01-18T18:11:04.759031Z	bruce_hofman@yahoo.com	https://api.calendly.com/scheduled
6465	2026-01-18T18:11:25.723491	calendly_webhook	2026-01-18T18:11:25.000000Z	https://api.calendly.com/users/8ec9d4df-39c5-4...	invitee.created	https://calendly.com/cancellations/4d3b1ca1-20...	2026-01-18T18:11:24.426405Z	bruce_hofman@yahoo.com	https://api.calendly.com/scheduled
6498	2026-01-18T08:55:43.745930	calendly_webhook	2026-01-18T08:55:43.000000Z	https://api.calendly.com/users/8ec9d4df-39c5-4...	invitee.created	https://calendly.com/cancellations/d273404a-69...	2026-01-18T08:55:42.126713Z	d966768@gmail.com	https://api.calendly.com/scheduled
8558	2026-01-19T23:38:37.929269	calendly_webhook	2026-01-19T23:38:37.000000Z	https://api.calendly.com/users/8ec9d4df-39c5-4...	invitee.created	https://calendly.com/cancellations/0ebe9a37-dd...	2026-01-19T23:38:36.748628Z	cynthia.okumu1@gmail.com	https://api.calendly.com/scheduled
9582	2026-01-20T00:03:20.608205	calendly_webhook	2026-01-20T00:03:20.000000Z	https://api.calendly.com/users/8ec9d4df-39c5-4...	invitee.created	https://calendly.com/cancellations/d7eaaefc-0a...	2026-01-20T00:03:19.420357Z	izzy777@duck.com	https://api.calendly.com/scheduled

8 rows × 68 columns

Next, I filter the **TikTok** events and find that there are **0 events** related to this channel.

TikTok

```
df_fact_events[df_fact_events['data_payload_scheduled_event_event_type'] == 'https://api.calendly.com/event_types/bb339e98-7a67-4af2-b584-8dbf95564312']
```

0.0s Python

ingestion_time	source	data_created_at	data_created_by	data_event	data_payload_cancel_url	data_payload_created_at	data_payload_email	data_payload_event	data_payload_first_name	...	data_payload_scheduled_event_event_memberships_us

0 rows × 68 columns

Then, focus on another database, **fact_marketing**:

fact_marketing

```
# List all Parquet files in folder
files = glob.glob("../data/Silver/fact_marketing/*/*.parquet")
# display(files)

# Read and concatenate them
df_fact_marketing = pd.concat([pd.read_parquet(f, engine="fastparquet") for f in files], ignore_index=True)
display(df_fact_marketing.head())
df_fact_marketing.info()
```

1.3s

	spend_date	channel	spend
0	2025-12-16	youtube	622.83
1	2025-12-16	facebook	510.96
2	2025-12-16	tiktok	260.15
3	2025-12-17	youtube	775.06
4	2025-12-17	facebook	636.82

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 105 entries, 0 to 104
Data columns (total 3 columns):
 #   Column      Non-Null Count  Dtype
---  ------      --------------  -----
 0   spend_date  105 non-null    object
 1   channel     105 non-null    object
 2   spend       105 non-null    float64
dtypes: float64(1), object(2)
memory usage: 2.6+ KB
```

2-8- Data Quality Checks and Validation

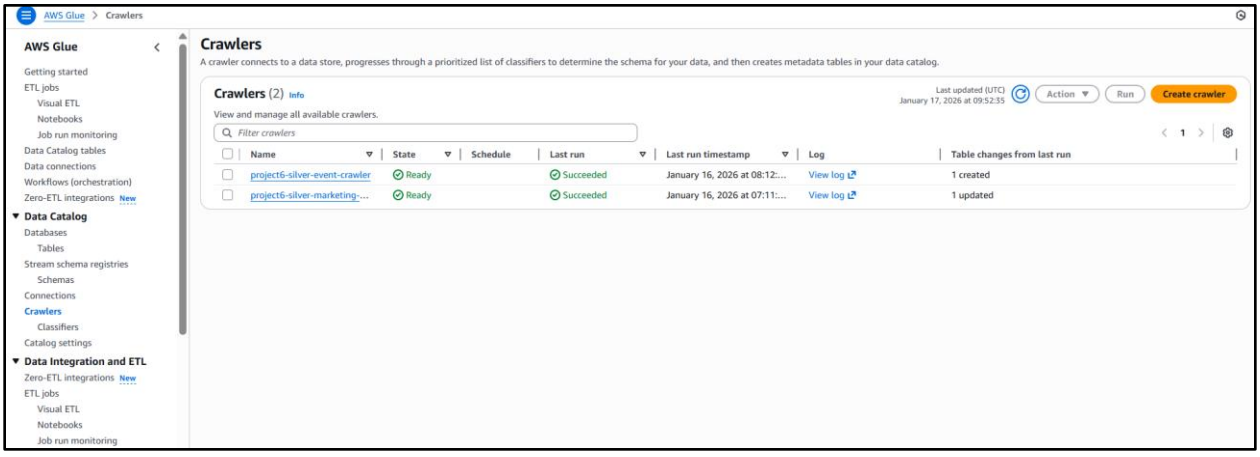
To ensure data integrity and reliability throughout the pipeline, several critical data quality checks and validations were implemented in the Silver layer. First, **not-null checks** were applied to primary keys, such as `invitee_id`, ensuring that all key fields are populated for successful data processing. Additionally, **deduplication logic** was employed to remove duplicate entries, particularly for booking events, by using business keys like `invitee_id` and `event_start_time`. **Timestamp sanity checks** were also introduced, verifying that the `event_created_at` timestamp does not exceed the ingestion time, thereby avoiding future-dated or incorrectly ordered events. For the **marketing spend data**, **spend validation** was applied to guarantee that all spend values are greater than or equal to zero, ensuring accurate calculations of **Cost Per Booking (CPB)**. Finally, any records failing these validation checks are conceptually **quarantined** into a designated *rejected* dataset, allowing for manual inspection and preventing invalid data from propagating through the pipeline. This multi-tiered approach ensures that the data is clean, consistent, and ready for reliable analytics in the downstream Gold layer.

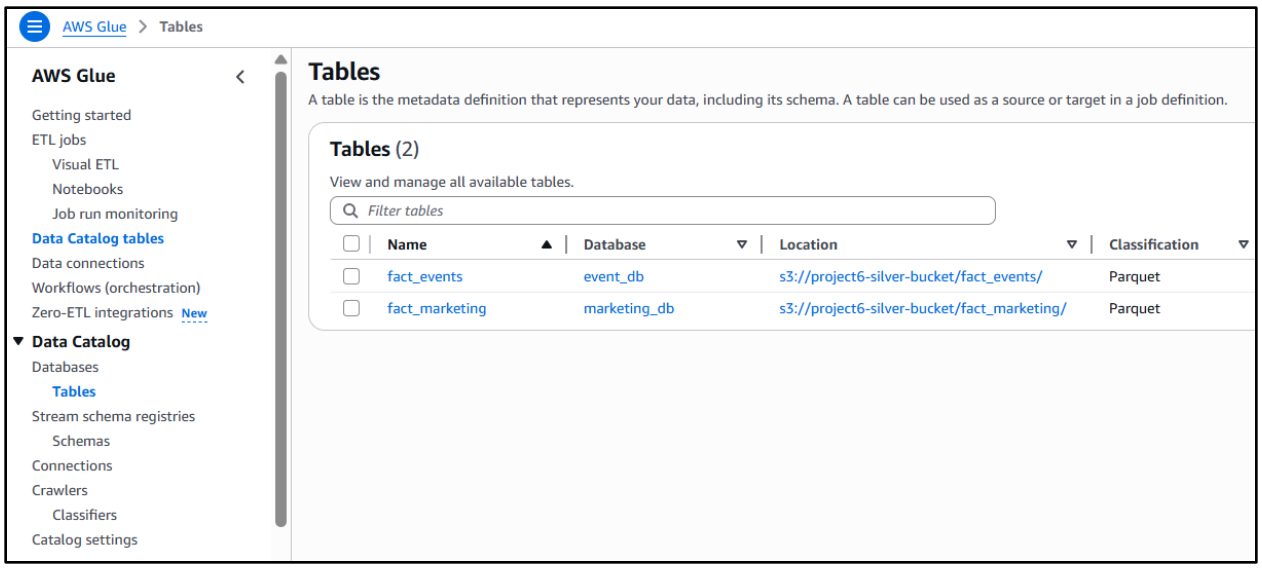
- Not-null checks
- Deduplication logic
- Timestamp sanity checks
- Spend validation (≥ 0)
- Mention rejected/quarantined records (even conceptually)

2-9- Silver Layer Data Validation Using Amazon Athena

In addition to local validation, the Silver layer data was also validated directly within AWS using **AWS Glue Crawlers** and **Amazon Athena**. Two AWS Glue Crawlers were created to catalog the Silver layer datasets stored in the **fact_events** and **fact_marketing** folders within the Silver S3 bucket. These crawlers automatically inferred the schema and registered the corresponding tables in the AWS Glue Data Catalog:

- **Database: event_db** **Table Name: fact_events**
- **Database: marketing_db** **Table Name: fact_marketing**

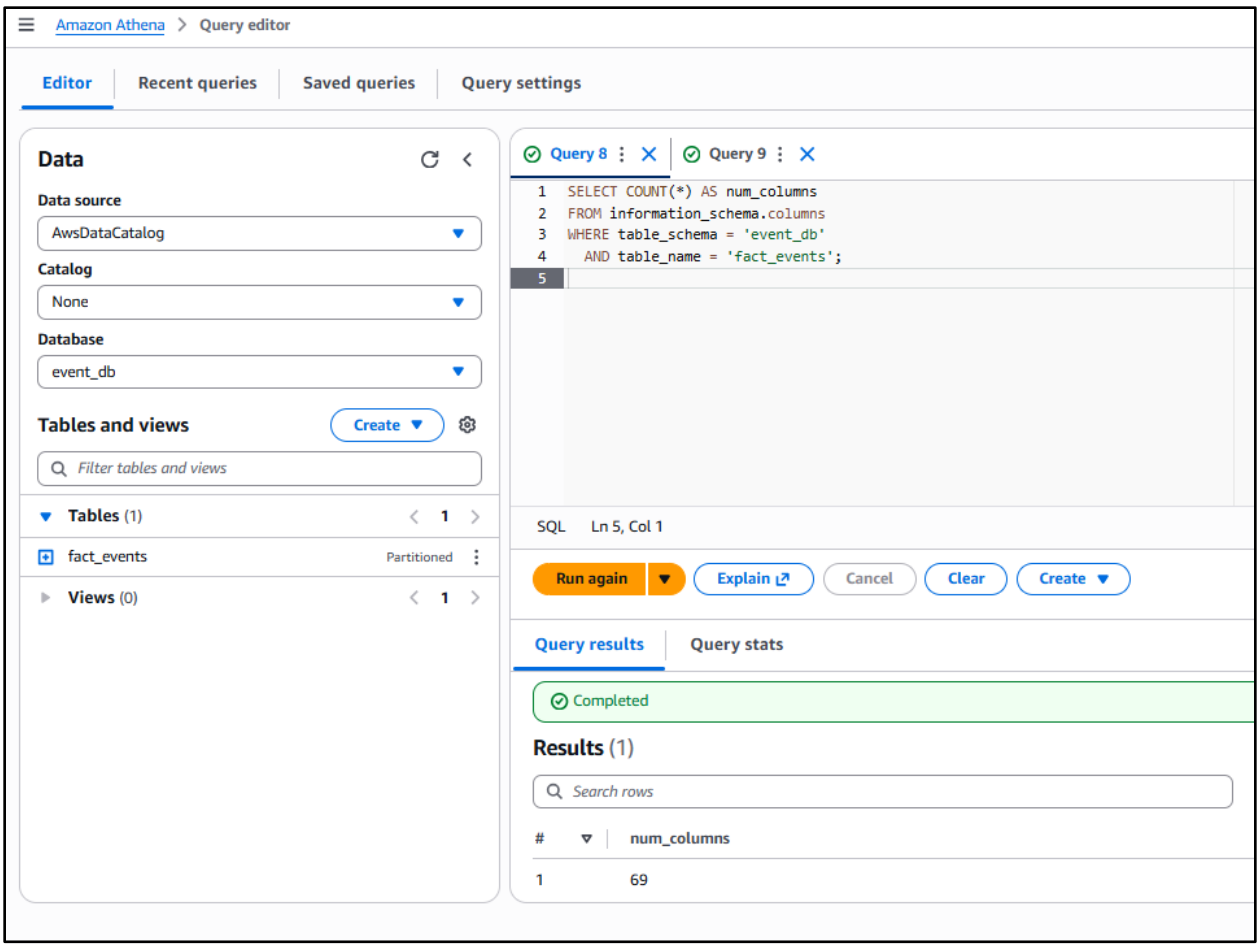




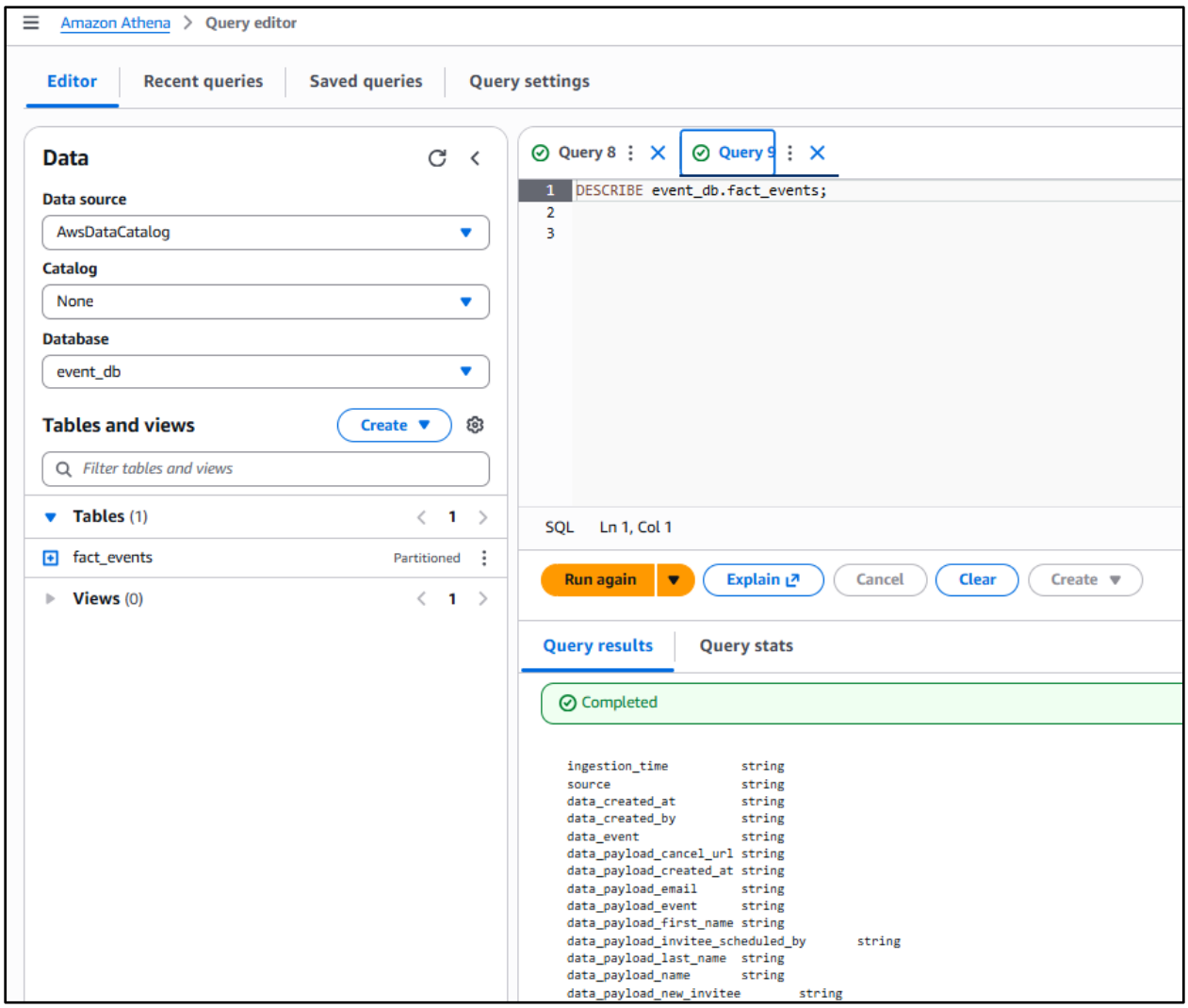
After the tables were created in the **Glue Data Catalog**, **Amazon Athena** was used to query the **Silver layer data**. Athena queries were executed to verify schema correctness, partition recognition, record counts, and data consistency across different partitions. Sample analytical queries, including row counts and filtered selections by date, were run successfully without errors, confirming that the Silver layer data was properly structured and accessible for downstream analytics.

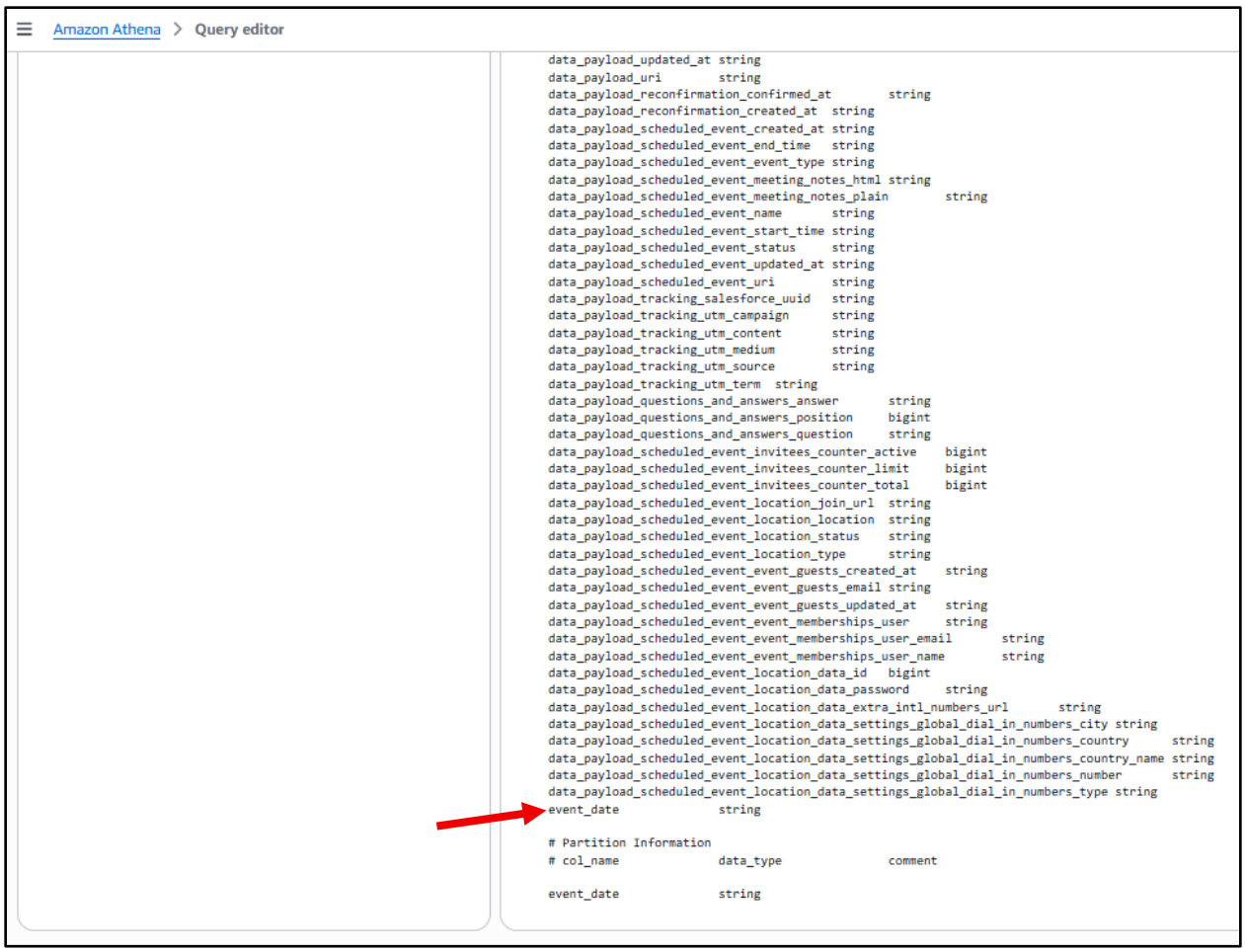
This validation step ensured that the Silver layer datasets were fully queryable using serverless SQL, accurately reflected the underlying Delta-generated Parquet files, and were ready for further processing and analysis in the Gold layer.

In Athena, first I did several queries on **fact_events** table. I was looking number of fileds on this table. As you saw above, the **Pandas Dataframe** shows there are only **68 columns**. It did not consider the Delta partitioning column. But here in **Amazon Athena**, it reads the Delta Table and shows number of fields as **69 columns**.

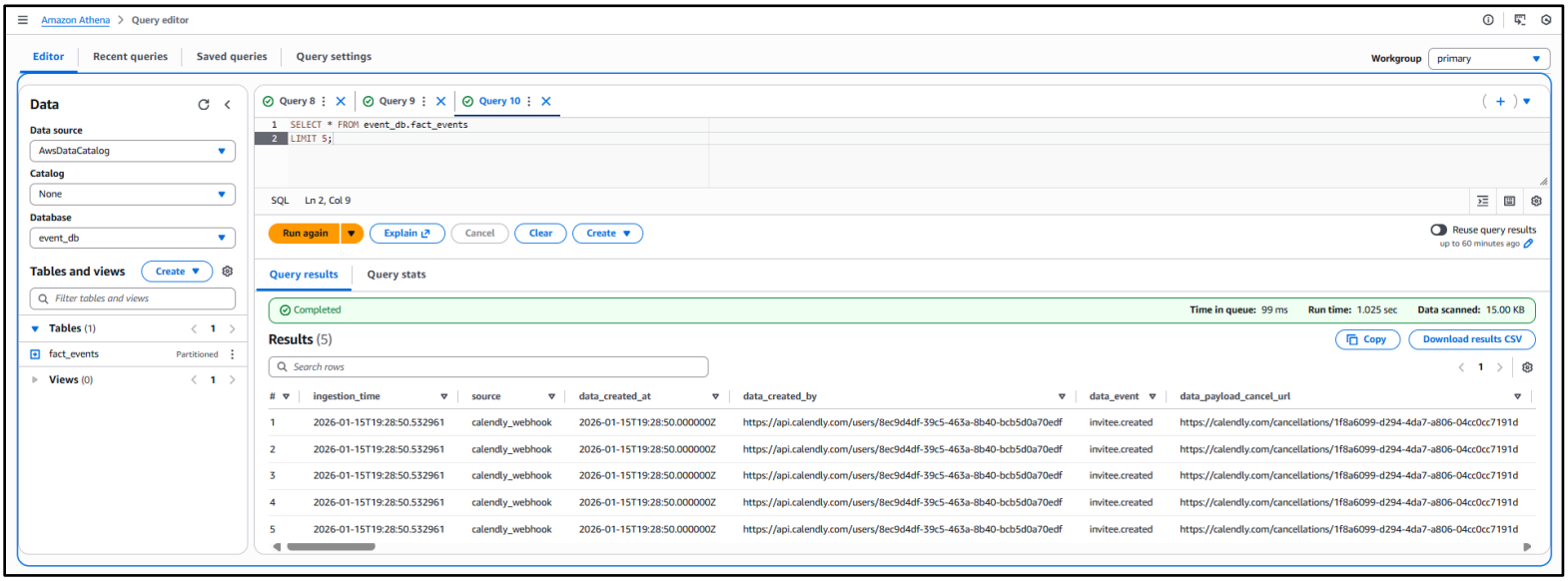


When I describe the database, I can see the last field is **event_date**, which is the partition key for this Delta Table.

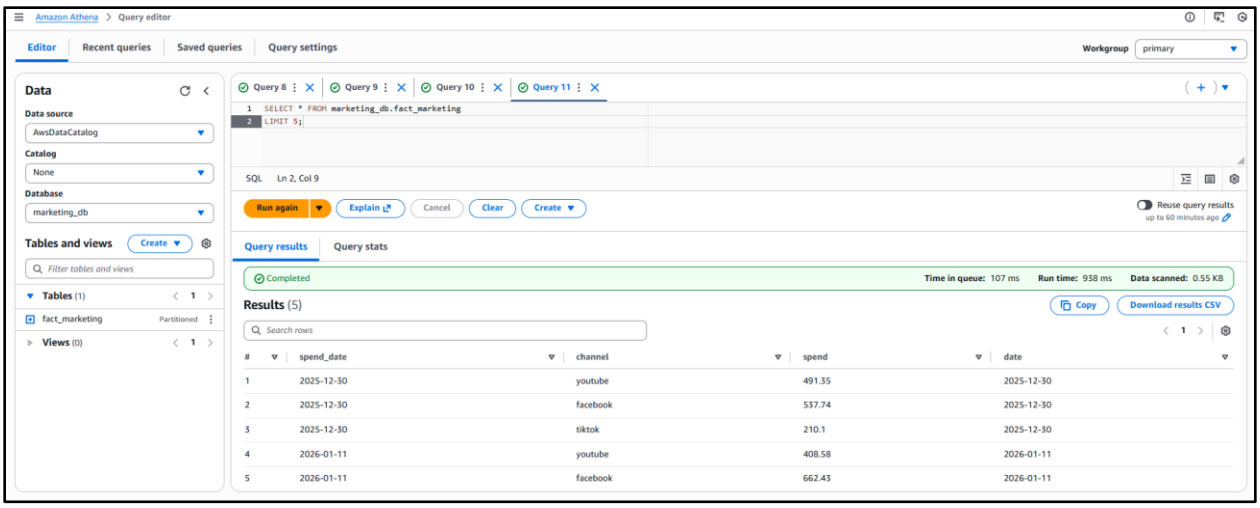

Amazon Athena
Query editor
Editor
Recent queries
Saved queries
Query settings
Data
Data source
AwsDataCatalog
Catalog
None
Database
event_db
Tables and views
Create
Filter tables and views
Tables (1)
fact_events
Partitioned
Views (0)
Query 8
Query 9
1 DESCRIBE event_db.fact_events;
2
3
SQL
Ln 1, Col 1
Run again
Explain
Cancel
Clear
Create
Query results
Query stats
Completed
ingestion_time string
source string
data_created_at string
data_created_by string
data_event string
data_payload_cancel_url string
data_payload_created_at string
data_payload_email string
data_payload_event string
data_payload_first_name string
data_payload_invitee_scheduled_by string
data_payload_last_name string
data_payload_name string
data_payload_new_invitee string



Then look at the header of this table:



After that I did a query on **fact_marketing** table.



So, everything is OK with queries, and the Silver layer data are validated successfully.

Step 3 – Analytics & Aggregation (S3 Gold Layer)

3-1- Objective

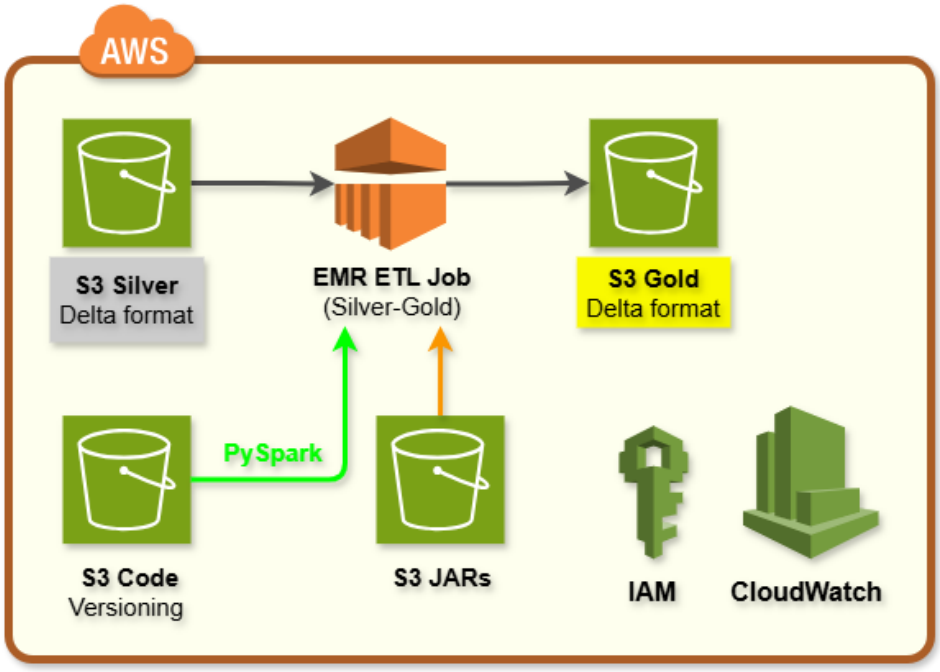
The objective of the **Gold layer** is to transform the curated Silver layer datasets into **business-focused, analytics-ready tables** that directly support reporting, KPI calculation, and decision-making. This layer is designed to aggregate, enrich, and join **events** and **marketing** datasets to produce meaningful metrics that answer core business questions related to marketing performance, lead conversion efficiency, and meeting utilization.

In the Gold layer, data is modeled around business use cases rather than raw events, enabling efficient computation of key performance indicators such as daily bookings by source, cost per booking (CPB) by channel, booking trends over time, channel attribution, time-based booking patterns, and employee meeting load. These transformations involve aggregations, joins between **Calendly events** and **marketing spend data**, and **derivation of time-based dimensions** (date, hour, day of week, and week).

All Gold layer outputs are stored as **Delta tables on top of Amazon S3**, ensuring transactional reliability, schema enforcement, and optimized query performance for downstream analytics. By maintaining a clean separation between Silver (data quality and standardization) and Gold (business logic and metrics), the architecture promotes scalability, reusability, and clear ownership of business definitions.

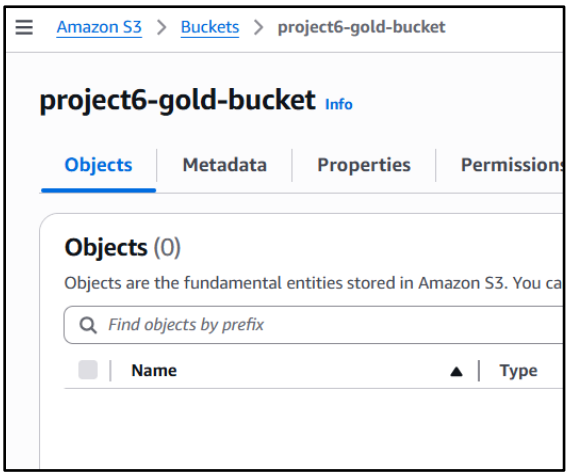
The Gold layer serves as the single source of truth for analytics and visualization, feeding Amazon **Athena queries** and the **Streamlit dashboard**, and enabling stakeholders to gain actionable insights into marketing effectiveness, booking behavior, and operational workload.

This is the Architecture of Gold Layer:

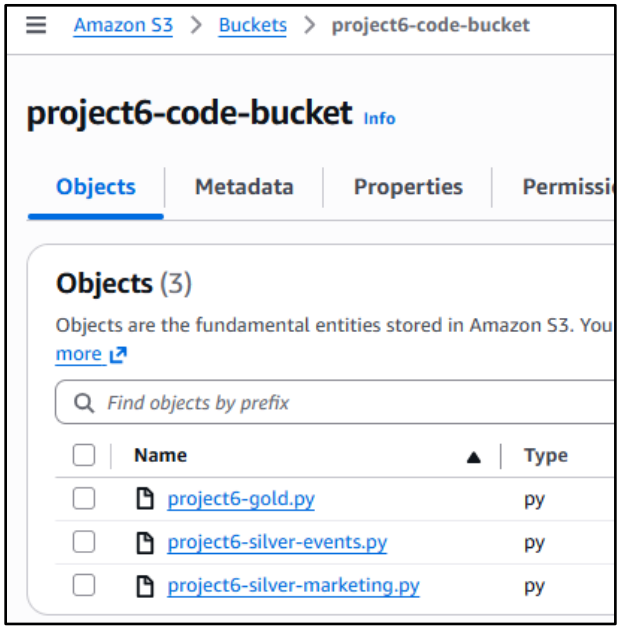


3-2- S3 Gold Layer

I used the Amazon S3 service to create a bucket named **s3://project6-gold-bucket/** to store the curated, business-ready datasets produced in the Gold layer. Data from the Silver layer Delta tables is further aggregated, enriched, and optimized to support analytical queries and business intelligence use cases. In this layer, multiple fact datasets are joined and transformed into metric-driven tables that directly support reporting requirements such as cost per booking, daily bookings by channel, and trend analysis. The resulting datasets are stored in Delta Lake format, ensuring data consistency, ACID compliance, and efficient query performance. The Gold layer is structured around analytics-ready tables, enabling seamless consumption by downstream tools such as **AWS Athena** and **Streamlit dashboards**.



Also, as EMR Serverless requires transformation scripts to be written externally in **PySpark** and **stored in an Amazon S3 location**, with the script path explicitly provided at job submission time, I add a new PySpark script to this bucket: **project6-gold.py**. This script is responsible for creating a few tables in the Gold layer in the Delta-formatted datasets.



3-3- Partition Strategy for Gold Delta Lake Tables

For optimal query performance in the Gold layer, Delta Lake tables are partitioned by `booking_date`, a natural choice for time-based partitioning. This strategy ensures that queries filtering on specific date ranges, such as daily, weekly, or monthly aggregations, only scan the relevant partitions, which significantly reduces I/O and boosts processing efficiency. Given that time-based queries are common in analytics, partitioning by `booking_date` streamlines data retrieval and improves overall performance. Additionally, **low-cardinality partitions** were chosen for `booking_date` to avoid excessive partition creation, which can occur if high-cardinality fields like `invitee_id` were used. This thoughtful partitioning approach strikes the right balance between **efficient query performance** and **manageable storage overhead**, ensuring that the data remains accessible and optimized for complex analytics.

3-4- EMR Job (Silver - Gold)

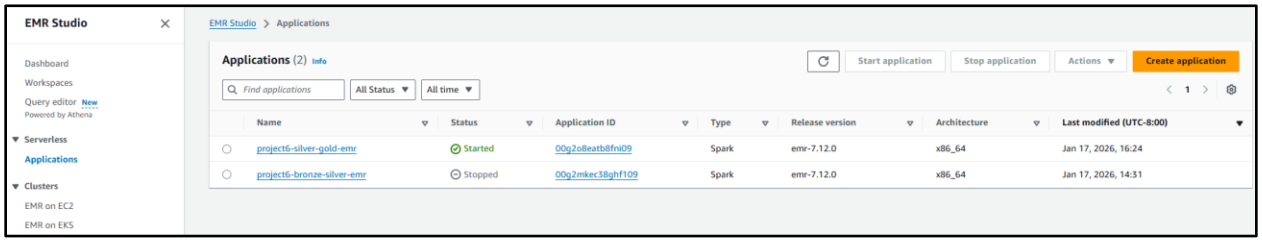
For the Gold layer, **EMR Serverless job** process curated Silver-layer datasets into business-ready, aggregated tables such as daily bookings by channel, cost per booking (CPB), and channel attribution.

Amazon EMR offers two deployment models: **EMR on EC2** and **EMR Serverless**. Again, EMR Serverless was chosen because it eliminates infrastructure management, scales automatically with workload, and provides cost-efficient execution, while delivering the performance and flexibility needed to transform **Delta Lake tables** for downstream analytics and visualization. EMR Serverless provides native Delta Lake support, enabling ACID-compliant writes, incremental updates, schema evolution, and efficient partition handling.

I started to create another EMR Serverless ETL job for aggregation of data from S3 Silver bucket. In AWS console, I clicked on the **EMR Serverless**, then clicked on **Create application (or manage the available applications)**. After that in the **EMR Studio** page, I am trying to create an EMR Serverless application. I filled in the application form as below:

- **Name:** **project6-silver-gold-emr**
- **Type:** Spark
- **Spark version:** 7.12.0 (matches Glue 4.0 and Delta JAR)
- **Execution role:** IAM role (**project6-emr-role**)
- **Tag:** project: 6

I selected the **Use default settings for batch jobs only** icon and left other defaults and cliked **Create**. Then, I got an **Application ID**, which I will use to submit jobs.



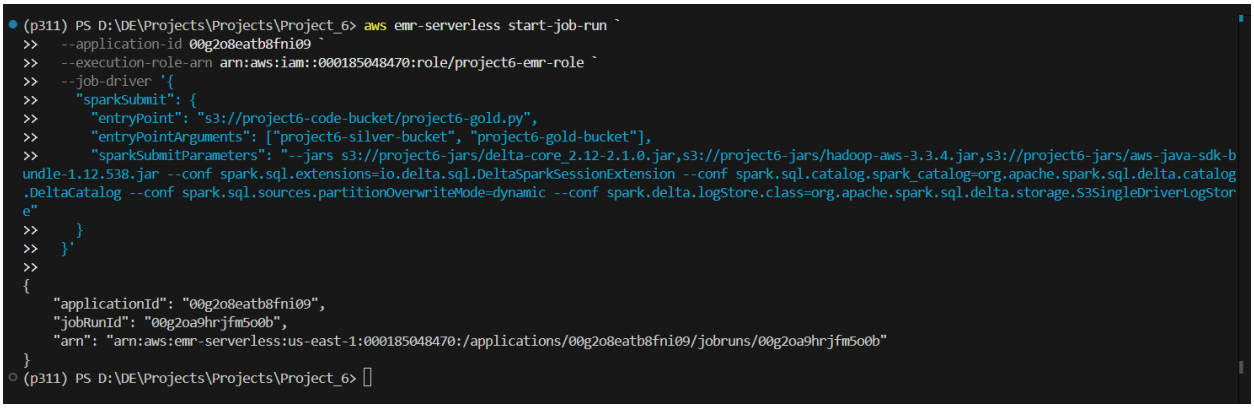
3-5- EMR ETL Job Submitting

Now, the EMR is ready to job sumitting. This job submission will be done using VS Code powershell. To sumbit the job I need this information:

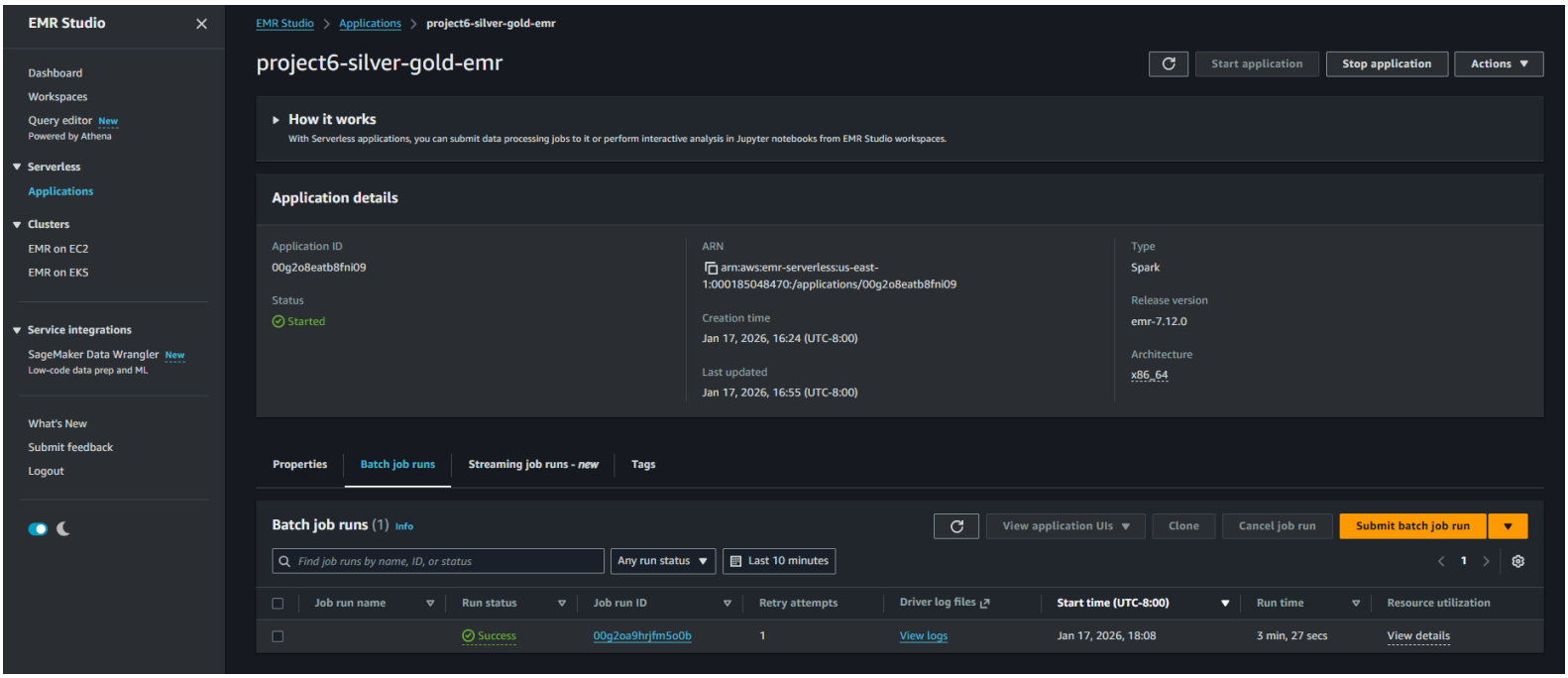
Parameters	Values	
Application-id	00g2o8eatb8fni09	
Execution-role-arn	arn:aws:iam::000185048470:role/project6-emr-role	
EntryPoint	s3://project6-code-bucket/project6-gold.py	
EntryPointArguments	["project6-silver-bucket", "project6-gold-bucket"]	
sparkSubmitParameters	**--jars**	s3://project6-jars/delta-core_2.12-2.1.0.jar, s3://project6-jars/hadoop-aws-3.3.4.jar, s3://project6-jars/aws-java-sdk-bundle-1.12.538.jar
	--conf	spark.sql.extensions=io.delta.sql.DeltaSparkSessionExtension
	--conf	spark.sql.catalog.spark_catalog=org.apache.spark.sql.delta.catalog.DeltaCatalog
	--conf	spark.sql.sources.partitionOverwriteMode=dynamic
	--conf	spark.delta.logStore.class=org.apache.spark.sql.delta.storage.S3SingleDriverLogStore

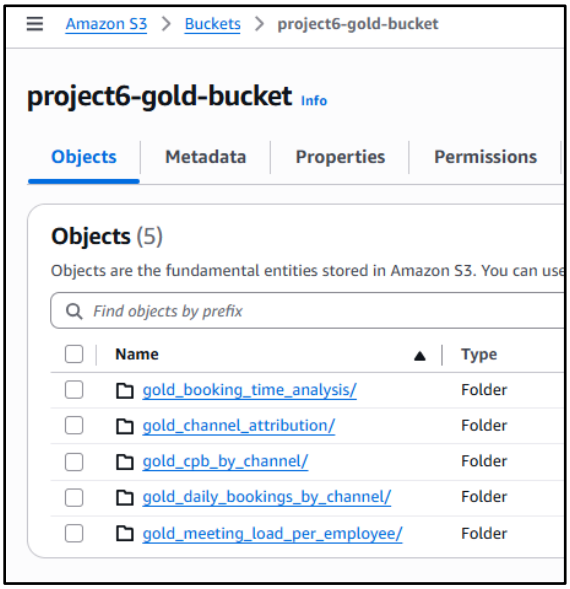
As I do not want to create specific folders in the Gold layer (unlike the Silver layer), then I used this job format to submit the job to EMR ETL in gold layer, which is changed a bit in entryPoint Arguments path:

```
aws emr-serverless start-job-run `
  --application-id 00g2o8eatb8fni09 `
  --execution-role-arn arn:aws:iam::000185048470:role/project6-emr-role `
  --job-driver '{
    "sparkSubmit": {
      "entryPoint": "s3://project6-code-bucket/project6-gold.py",
      "entryPointArguments": ["project6-silver-bucket", "project6-gold-bucket"],
      "sparkSubmitParameters": "--jars s3://project6-jars/delta-core_2.12-2.1.0.jar,s3://project6-
jars/hadoop-aws-3.3.4.jar,s3://project6-jars/aws-java-sdk-bundle-1.12.538.jar --conf
spark.sql.extensions=io.delta.sql.DeltaSparkSessionExtension --conf
spark.sql.catalog.spark_catalog=org.apache.spark.sql.delta.catalog.DeltaCatalog --conf
spark.sql.sources.partitionOverwriteMode=dynamic --conf
spark.delta.logStore.class=org.apache.spark.sql.delta.storage.S3SingleDriverLogStore"
    }
  }'
```



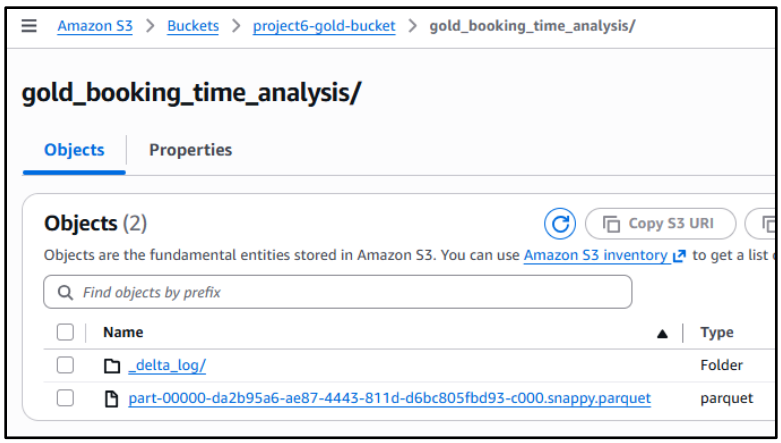
The job is successfully submitted and runned.





There are five folders (Delta Tables) in the Gold bucket and inside each of them are like this:

- **_delta_log/** folder
- **Parquet** files for partitions



3-6- Gold Layer Data Validation Using AWS CLI

To validate the data in the Gold layer, all **Parquet** files (stored as Delta tables) were downloaded from the Gold S3 bucket to the local machine. The following AWS CLI commands were used to recursively copy only the Parquet files for each dataset:

```
gold_booking_time_analysis/
aws s3 cp s3://project6-gold-bucket/gold_booking_time_analysis/
./data/Gold/gold_booking_time_analysis/ --recursive --exclude "*" --include "*.parquet"

gold_cpb_by_channel/
aws s3 cp s3://project6-gold-bucket/gold_cpb_by_channel/ ./data/Gold/gold_cpb_by_channel/ --
recursive --exclude "*" --include "*.parquet"

gold_channel_attribution/
aws s3 cp s3://project6-gold-bucket/gold_channel_attribution/
./data/Gold/gold_channel_attribution/ --recursive --exclude "*" --include "*.parquet"

gold_daily_bookings_by_channel/
aws s3 cp s3://project6-gold-bucket/gold_daily_bookings_by_channel/
./data/Gold/gold_daily_bookings_by_channel/ --recursive --exclude "*" --include "*.parquet"

gold_meeting_load_per_employee/
aws s3 cp s3://project6-gold-bucket/gold_meeting_load_per_employee/
./data/Gold/gold_meeting_load_per_employee/ --recursive --exclude "*" --include "*.parquet"
```

After downloading the Parquet files, the datasets were explored in a Jupyter Notebook using the Pandas library. The Parquet files were loaded into Pandas DataFrames and carefully reviewed to validate schema consistency, data integrity, and transformation correctness. The validation confirmed that the Gold layer data was successfully processed and met the expected quality standards. Screenshots of five representative DataFrames are provided below.

1) gold_booking_time_analysis

```python
# List all Parquet files in folder
files = glob.glob("../data/Gold/gold_booking_time_analysis/*.parquet")
display(files)

# Read and concatenate them
df_gold_booking_time_analysis = pd.concat([pd.read_parquet(f, engine="fastparquet") for f in files], ignore_index=True)
display(df_gold_booking_time_analysis.head())
df_gold_booking_time_analysis.info()
```

✓ 0.0s

```
['../data/Gold/gold_booking_time_analysis\\part-00000-e0288799-c164-4e85-b97a-852401db9d45-c000.snappy.parquet',
 '../data/Gold/gold_booking_time_analysis\\part-00002-4a87abae-5921-4880-b4f2-4603c73d585a-c000.snappy.parquet',
 '../data/Gold/gold_booking_time_analysis\\part-00005-18896e56-3920-4c31-aa17-7bdc2c2f7fe5-c000.snappy.parquet',
 '../data/Gold/gold_booking_time_analysis\\part-00008-d2230bae-9638-41c8-b72c-1fcdfbeac2ec-c000.snappy.parquet',
 '../data/Gold/gold_booking_time_analysis\\part-00011-4d9cc4f8-543b-4133-8a7d-63366c3ab74d-c000.snappy.parquet']
```

	channel	booking_hour	booking_day_of_week	bookings_count
0	facebook	16.0	5.0	7
1	facebook	15.0	2.0	5
2	facebook	0.0	5.0	1
3	facebook	0.0	1.0	2
4	facebook	14.0	2.0	5

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 192 entries, 0 to 191
Data columns (total 4 columns):
 #   Column               Non-Null Count  Dtype
---  ------               --------------  -----
 0   channel              192 non-null    object
 1   booking_hour         191 non-null    float64
 2   booking_day_of_week  191 non-null    float64
 3   bookings_count       192 non-null    int64
dtypes: float64(2), int64(1), object(1)
memory usage: 6.1+ KB
```

I classified the channels into four groups: [**'facebook'**, **'youtube'**, **'tiktok'**, **'others'**]. If I filter only the **YouTube**, then I can see the details.

2) gold_cpb_by_channel

```
# List all Parquet files in folder
files = glob.glob("../data/Gold/gold_cpb_by_channel/*.parquet")
display(files)

# Read and concatenate them
df_gold_cpb_by_channel = pd.concat([pd.read_parquet(f, engine="fastparquet") for f in files], ignore_index=True)
display(df_gold_cpb_by_channel.head())
df_gold_cpb_by_channel.info()
```

✓ 0.0s

```
['../data/Gold/gold_cpb_by_channel\\part-00000-fde0fbbd-affd-494c-9172-75679f25077d-c000.snappy.parquet']
```

	channel	total_bookings_count	total_spend	cpb
0	others	9330	0.00	0.00000
1	facebook	283	20260.42	71.59159
2	youtube	8	20207.43	2525.92875
3	tiktok	0	13593.57	0.00000

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 4 entries, 0 to 3
Data columns (total 4 columns):
 #   Column               Non-Null Count  Dtype
---  ------               --------------  -----
 0   channel              4 non-null      object
 1   total_bookings_count  4 non-null      int64
 2   total_spend          4 non-null      float64
 3   cpb                  4 non-null      float64
dtypes: float64(2), int64(1), object(1)
memory usage: 260.0+ bytes
```

3) gold_channel_attribution

```python
# List all Parquet files in folder
files = glob.glob("../data/Gold/gold_channel_attribution/*.parquet")
display(files)

# Read and concatenate them
df_gold_channel_attribution = pd.concat([pd.read_parquet(f, engine="fastparquet") for f in files], ignore_index=True)
display(df_gold_channel_attribution.head())
df_gold_channel_attribution.info()
```

✓ 0.0s

```
['../data/Gold/gold_channel_attribution\\part-00000-6d7ad8b8-e485-4894-84f3-a20472136a1b-c000.snappy.parquet']
```

	channel	total_bookings_count	total_spend	cpb	rank_by_volume	rank_by_cpb
0	others	9330	0.00	0.00000	1	1
1	tiktok	0	13593.57	0.00000	4	1
2	facebook	283	20260.42	71.59159	2	2
3	youtube	8	20207.43	2525.92875	3	3

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 4 entries, 0 to 3
Data columns (total 6 columns):
 #   Column                Non-Null Count  Dtype
---  ------                --------------  -----
 0   channel               4 non-null      object
 1   total_bookings_count  4 non-null      int64
 2   total_spend           4 non-null      float64
 3   cpb                   4 non-null      float64
 4   rank_by_volume        4 non-null      int32
 5   rank_by_cpb           4 non-null      int32
dtypes: float64(2), int32(2), int64(1), object(1)
memory usage: 292.0+ bytes
```

4) gold_daily_bookings_by_channel

```python
# List all Parquet files in folder
files = glob.glob("../data/Gold/gold_daily_bookings_by_channel/*.parquet")
display(files)

# Read and concatenate them
df_gold_daily_bookings_by_channel = pd.concat([pd.read_parquet(f, engine="fastparquet") for f in files], ignore_index=True)
display(df_gold_daily_bookings_by_channel.head())
df_gold_daily_bookings_by_channel.info()
```

✓ 0.0s

```
['../data/Gold/gold_daily_bookings_by_channel\\part-00000-9a76f5d6-e8ac-4cbd-8ec0-9c7c0d2fa8ab-c000.snappy.parquet',
 '../data/Gold/gold_daily_bookings_by_channel\\part-00002-79185500-1410-432c-9b97-f6340a54b552-c000.snappy.parquet',
 '../data/Gold/gold_daily_bookings_by_channel\\part-00005-f96788ce-6eae-4933-92a4-528841af9d71-c000.snappy.parquet',
 '../data/Gold/gold_daily_bookings_by_channel\\part-00008-db7d6af0-22c6-4fbe-9c1f-e3574cf6eee1-c000.snappy.parquet',
 '../data/Gold/gold_daily_bookings_by_channel\\part-00011-f9671050-1a8b-47c0-8a22-230b7bd0adfe-c000.snappy.parquet']
```

	booking_date	channel	bookings_count	booking_week
0	2026-01-18	facebook	27	3
1	2026-01-25	facebook	0	4
2	2026-02-13	facebook	0	7
3	2026-01-14	facebook	13	3
4	2026-01-31	facebook	0	5

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 116 entries, 0 to 115
Data columns (total 4 columns):
 #   Column          Non-Null Count  Dtype
---  ------          --------------  -----
 0   booking_date    116 non-null    datetime64[ns]
 1   channel         116 non-null    object
 2   bookings_count  116 non-null    int64
 3   booking_week    116 non-null    int32
dtypes: datetime64[ns](1), int32(1), int64(1), object(1)
memory usage: 3.3+ KB
```

5) gold_meeting_load_per_employee

```
# List all Parquet files in folder
files = glob.glob("../data/Gold/gold_meeting_load_per_employee/*.parquet")
display(files)

# Read and concatenate them
df_gold_meeting_load_per_employee = pd.concat([pd.read_parquet(f, engine="fastparquet") for f in files], ignore_index=True)
display(df_gold_meeting_load_per_employee.head())
df_gold_meeting_load_per_employee.info()
```

✓ 0.0s

```
['../data/Gold/gold_meeting_load_per_employee\\part-00000-7f216ed2-6ec5-4262-a231-f2e14e6159c3-c000.snappy.parquet']
```

	user_id	total_meetings_count
0	030a66c4-ad31-42a1-9568-fda1cf399cef	24
1	da226a81-f340-42b1-87b6-adf44d649dd3	19
2	b7a24d00-d0eb-495f-bb86-241ede6e81f2	20
3	98c10b79-1c4d-4135-8bd6-48bf7ec14925	391
4	e03e8f12-1a32-48e5-b01f-1a5996a50f10	19

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 61 entries, 0 to 60
Data columns (total 2 columns):
 #   Column               Non-Null Count  Dtype 
---  ------               --------------  ----- 
 0   user_id              61 non-null     object
 1   total_meetings_count  61 non-null     int64 
dtypes: int64(1), object(1)
memory usage: 1.1+ KB
```

So, everything is OK with Delta Tables in the Gold layer and are validated successfully.

Step 4 – Jobs Orchestration and CI/CD

4-1- Objective

The objective of the CI/CD approach is to automate the end-to-end batch data pipeline on a daily schedule, while ensuring reliable orchestration, well-defined job dependencies, and maintainable deployment practices. Both **real-time event data from the Calendly Webhook API** and **batch marketing data from the DEA public S3 bucket** are ingested into AWS, transformed across the **Bronze, Silver, and Gold layers**, and made available for analytics and visualization **without manual intervention**. Real-time Calendly events are ingested through **AWS Lambda functions exposed via Amazon API Gateway**, which automatically receive and process webhook events in near real time. Batch marketing data is ingested through a scheduled **AWS Glue job**.

To support continuous development and deployment, all **AWS Lambda, AWS Glue, and EMR Serverless scripts** are version-controlled in a GitHub repository and automatically deployed to AWS through a CI/CD workflow whenever changes are introduced.

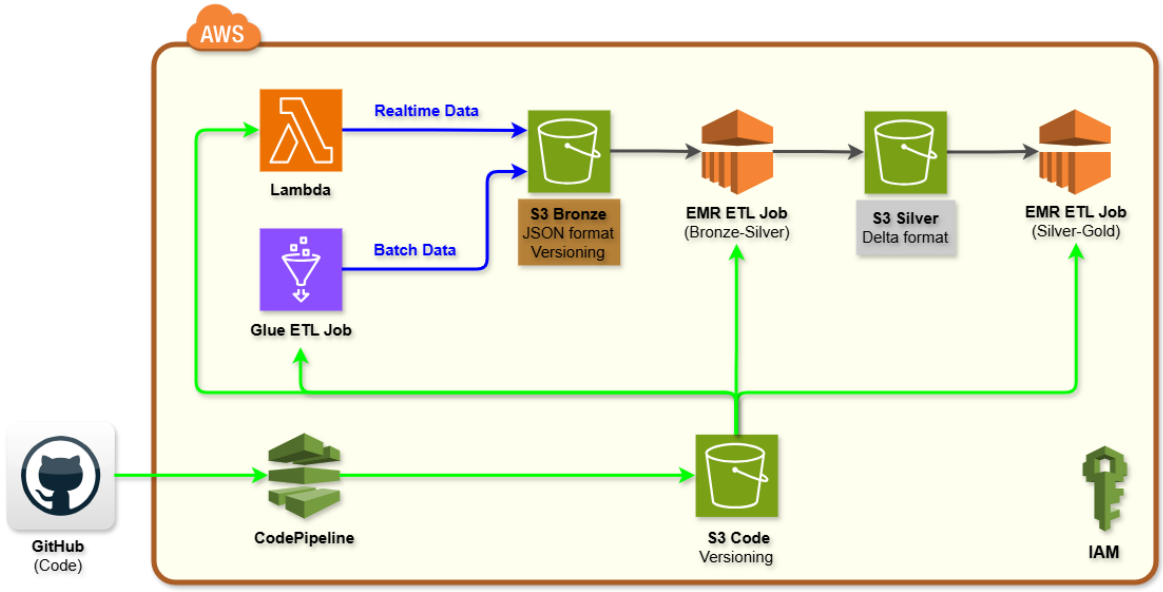
The pipeline is orchestrated using **AWS Step Functions**, which acts as the central control layer. On a daily schedule, a Glue job ingests marketing data into the Bronze layer, after which AWS Step Functions coordinates the execution of the Bronze-to-Silver and Silver-to-Gold transformation jobs in a dependency-driven sequence, ensuring data consistency, fault isolation, and reliable end-to-end processing.

4-2- CI/CD Strategy

This approach enables automated deployment, traceability, and reproducibility of data pipelines. All Python and PySpark scripts for Lambda function, Glue ETL job, and EMR Serverless ETL jobs are stored in a **GitHub** repository: https://github.com/Hadi2468/ELT_Project6/tree/main.

This design ensures:

- Clear and deterministic job dependencies
- Controlled execution order
- Parallel processing where appropriate
- Failure isolation and observability
- Minimal operational complexity
- Scalable and production-ready CI/CD practices

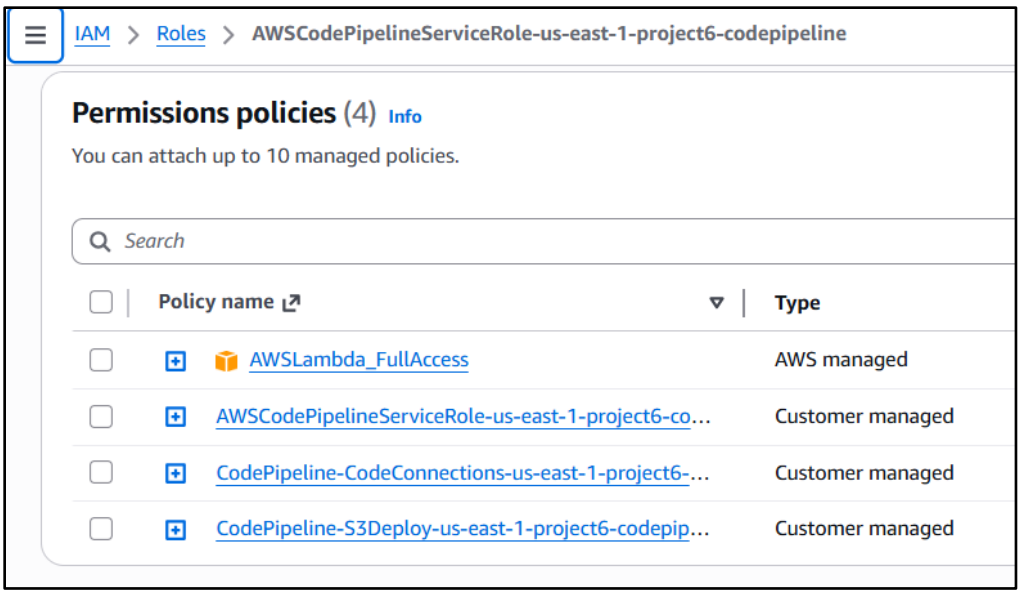


4-3- IAM Role

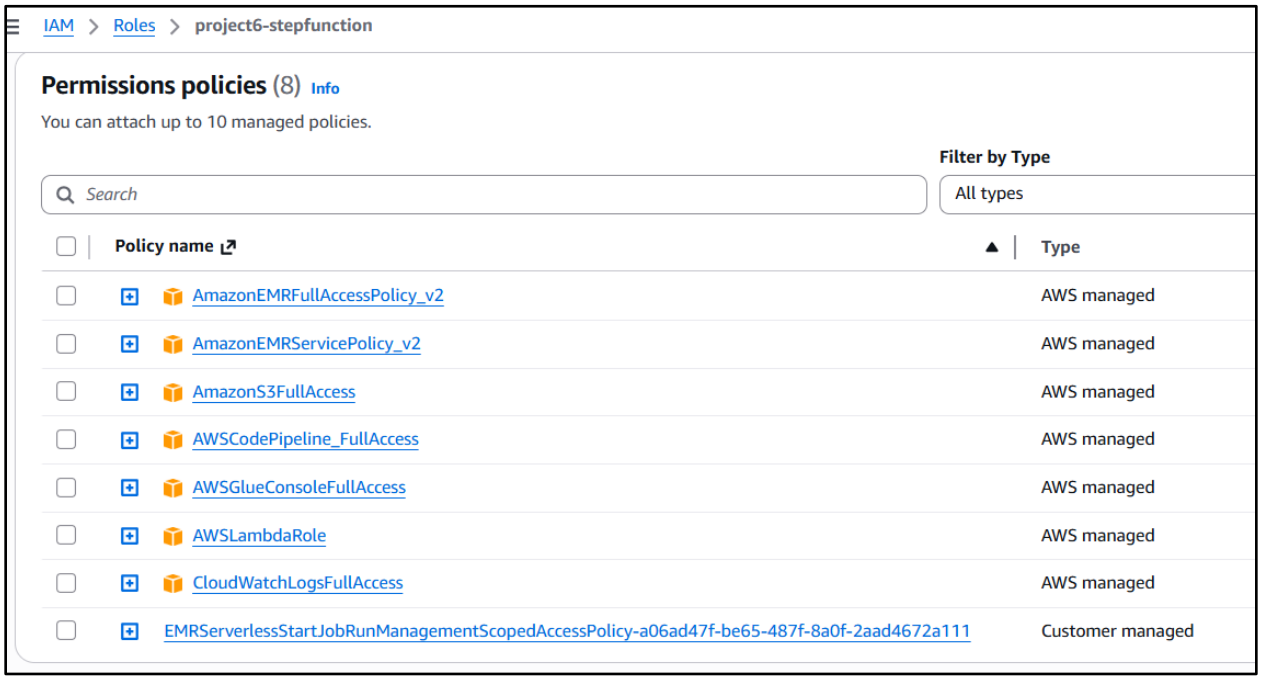
During setting up the AWS CodePipeline, it asked for an IAM role, and I configured **a new role**, and **I did not change its' name**, named **AWSCodePipelineServiceRole-us-east-1-project6-codepipeline** and tagged with **project: 6**. This role grants CodePipeline the required permissions to securely connect to the GitHub repository, retrieve the Python and PySpark source codes, and deploy the artifacts to Amazon S3. After that, I added a new "AWSLambda_FullAccess" policy to this role, as I want to trigget the CodePipeline with **Lambda Functiona** and using the **Step Functions** later.

The following permissions were configured:

- **AWSCodePipelineServiceRole**: Grants CodePipeline core permissions to orchestrate pipeline stages and interact with AWS services on behalf of the pipeline.
- **CodePipeline-CodeConnections**: Allows CodePipeline to establish and manage secure connections to external source providers such as GitHub using AWS CodeStar Connections.
- **CodePipeline-S3Deploy**: Provides permission for CodePipeline to upload, read, and manage build artifacts in Amazon S3 buckets used during the deployment process.
    - **AWSLambda_FullAccess**: Provides permission for CodePipeline to triggered by Lambda function.



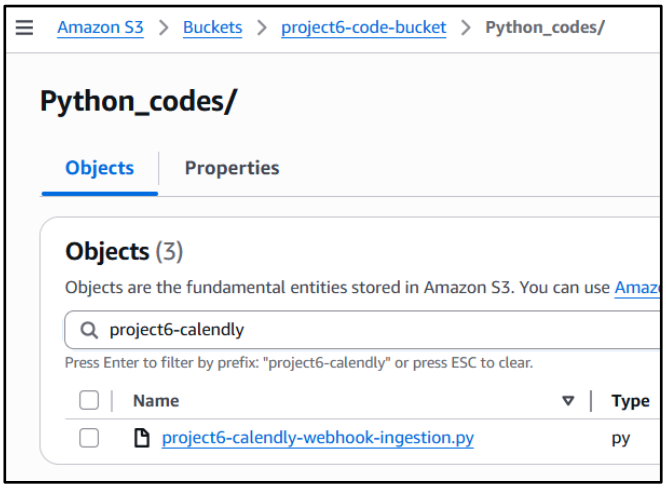
Also I need a comprehensive access permission for Step Functions, then I created a new IAM role, named **project6-stepfunction** and tagged with **project: 6**. This role grants Step Functions the required permissions to securely connect to all used AWS services in this project.

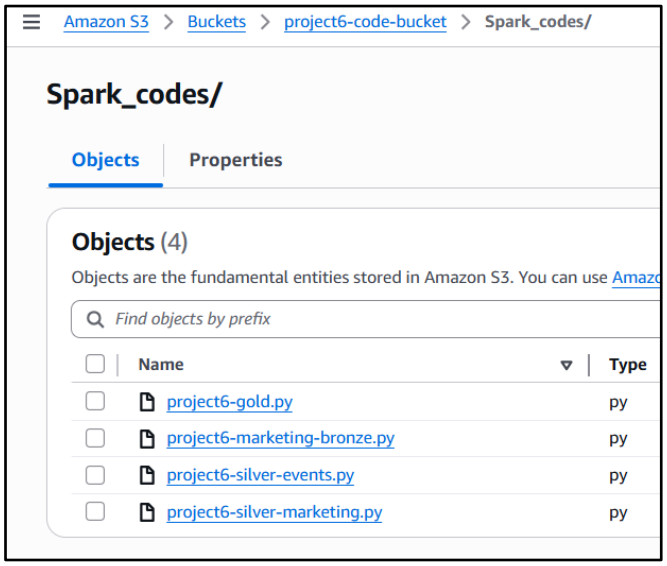


4-4- S3 Code Bucket

The CI/CD pipeline automatically detects changes or additions to Lambda function, Glue job, or EMR Serverless scripts in the GitHub repo and immediately deploys updated scripts to another S3 (code)

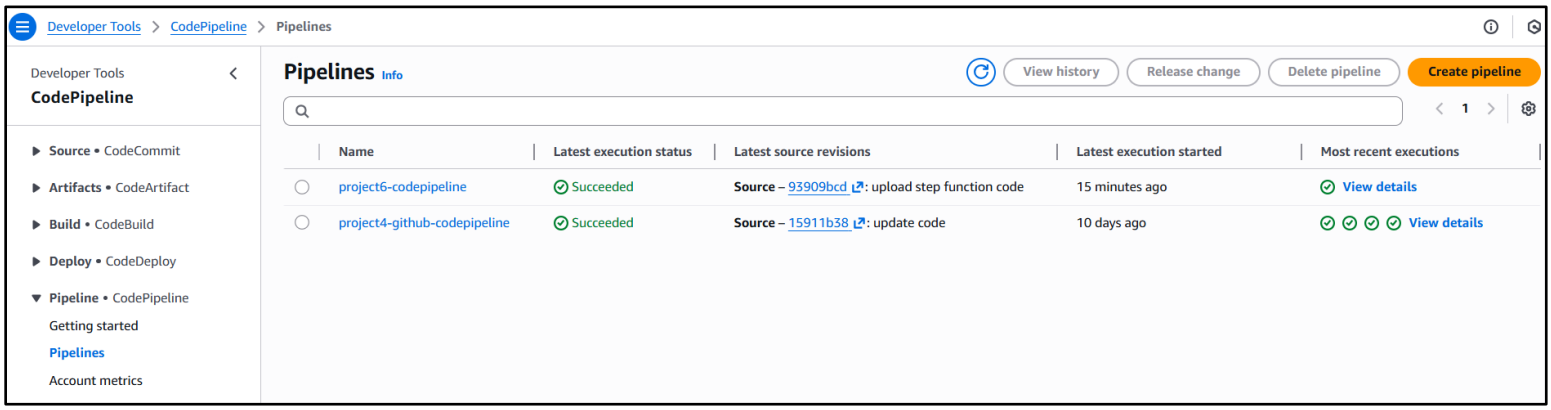
bucket, named **s3://project6-code-bucket/** using AWS CodePipeline service. All Python or PySpark jobs reference their scripts directly from the S3 code bucket, ensuring version consistency, easy rollback, and no manual code uploads. I have enabled its **versioning** option to store all versions of codes to support auditability, reprocessing, and downstream transformations.

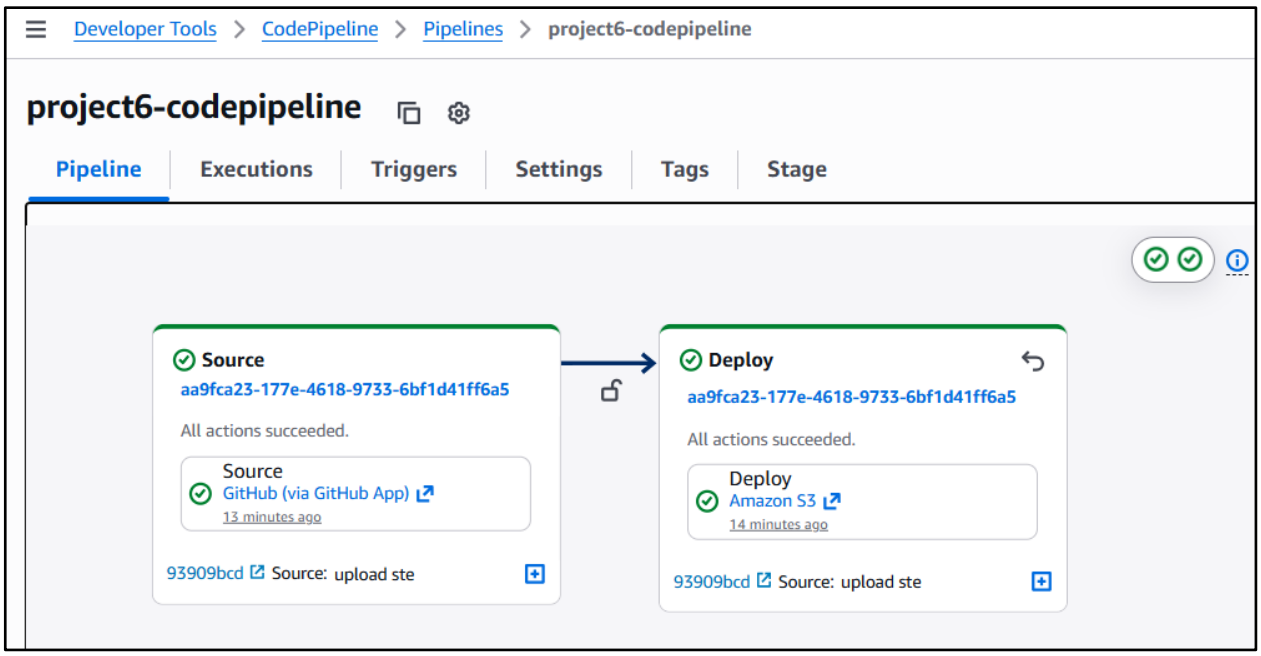




4-5- CodePipeline

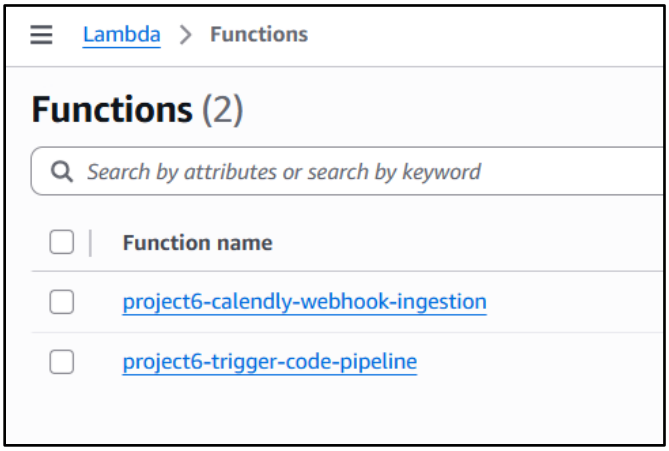
Then, I finished setting up the AWS CodePipeline and named it **project6-codepipeline** and tagged it with **project: 6**.

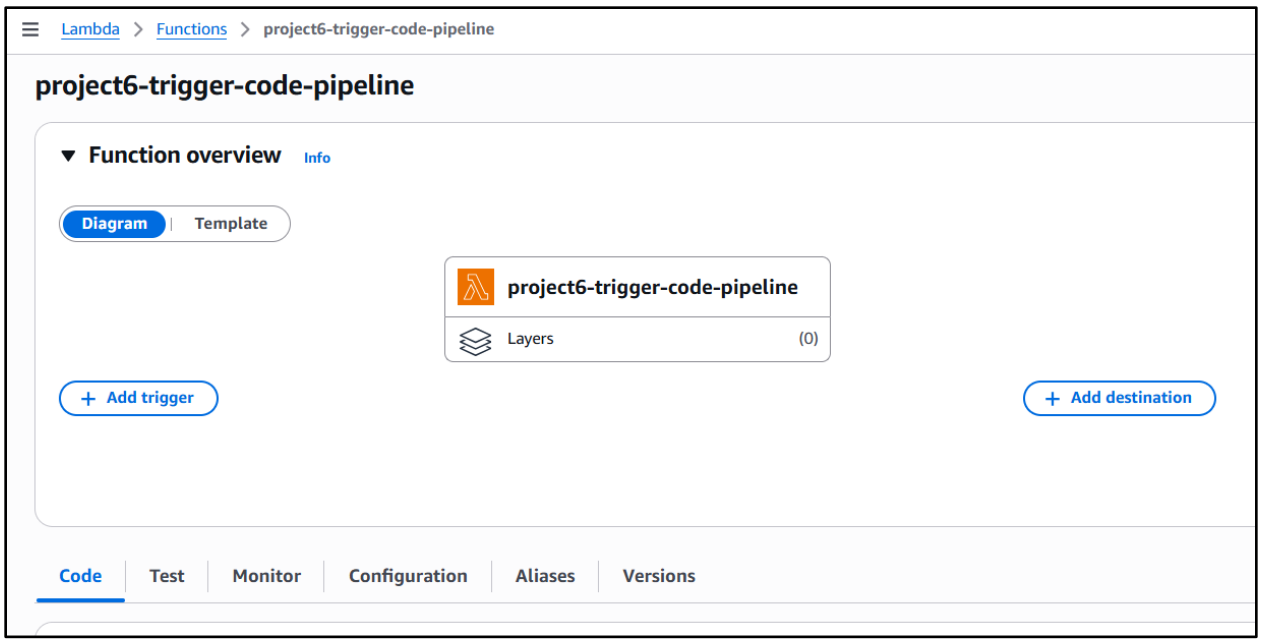




4-6- Lambda

I decided to put CodePipeline as a first step inside the Step Functions, to make sure everything was orchestrated well. Then, I need a simple Lambda function for triggering the CodePipeline. I named this function as **project6-trigger-code-pipeline**.





I used this script for Lambda function for triggering the CodePipeline:

```
import boto3

def lambda_handler(event, context):
    client = boto3.client("codepipeline")
    response = client.start_pipeline_execution(
        name="project6-codepipeline"
    )
    return response
```

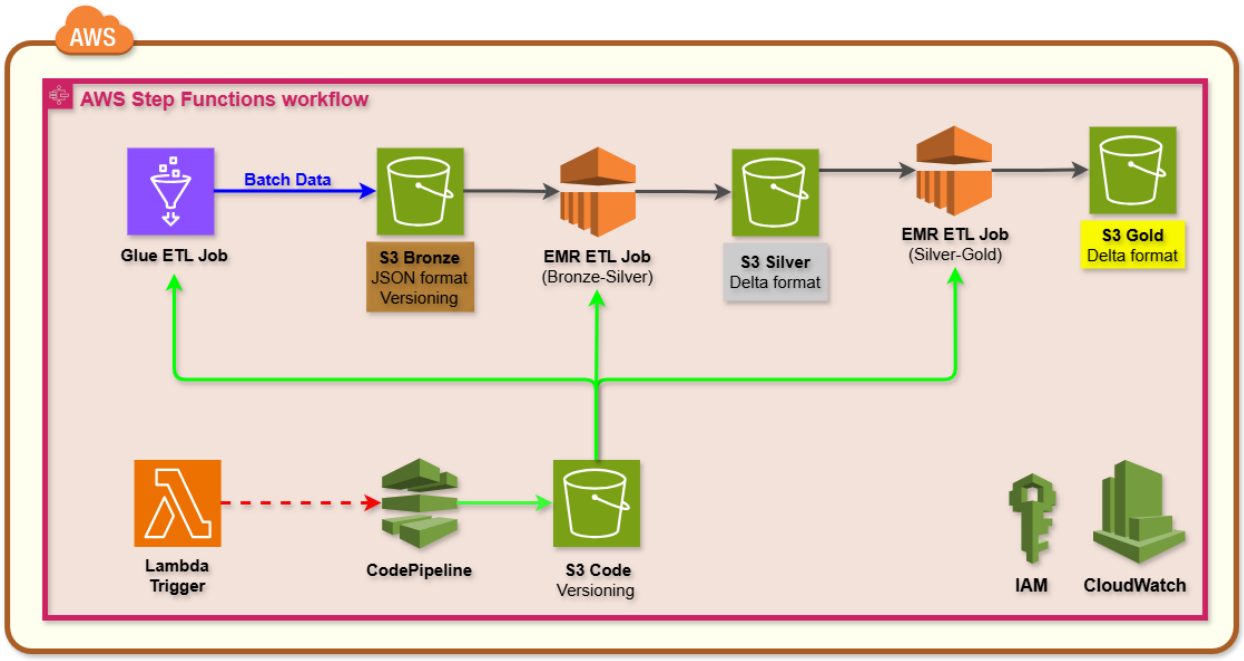
4-7- Orchestration (Step Functions)

For orchestration of the AWS Glue and EMR Serverless ETL jobs, an **AWS Step Functions state machine**, named **project6-state-machine**, is used as the central orchestration engine of the pipeline. This state machine triggered on a **daily schedule** using a **Step Functions time-based trigger** and is responsible for coordinating the execution of all batch processing jobs.

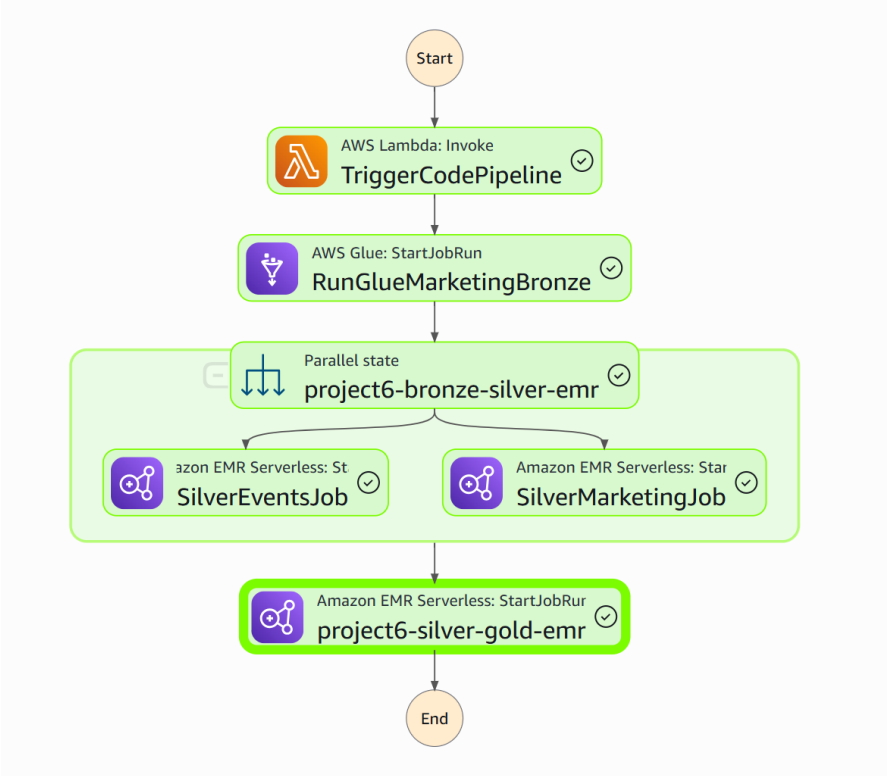
The state machine executes jobs in a **dependency-driven sequence**, ensuring that each processing stage completes successfully before the next stage begins. The execution flow is defined as follows:

Glue ETL Job (Data Ingestion to Bronze Layer) →
EMR Serverless ETL Job (Silver Layer Transformation) →
EMR Serverless ETL Job (Gold Layer Aggregation)

By centralizing orchestration within **AWS Step Functions**, the pipeline benefits from improved reliability, clear job dependencies, built-in error handling, and easier monitoring of end-to-end execution, making the overall architecture more robust and production-ready.



After creating Step Functions, I executed successfully and orchestrated well. Each step wents to be green after finishing, as you can see in this graph:



4-8- Monitoring and Failure Handling

To monitoring and failure handling, each Glue job writes logs (Output or Error) to **Amazon CloudWatch**. Then, in case of any job failure:

- The Lambda function, Glue ETL job, EMR Serverless ETL jobs stops downstream execution
- Error details are available in CloudWatch Logs for troubleshooting

Also, we can follow all logging messages that I created in each block of the code, like Start states, Success, or Exceptions.

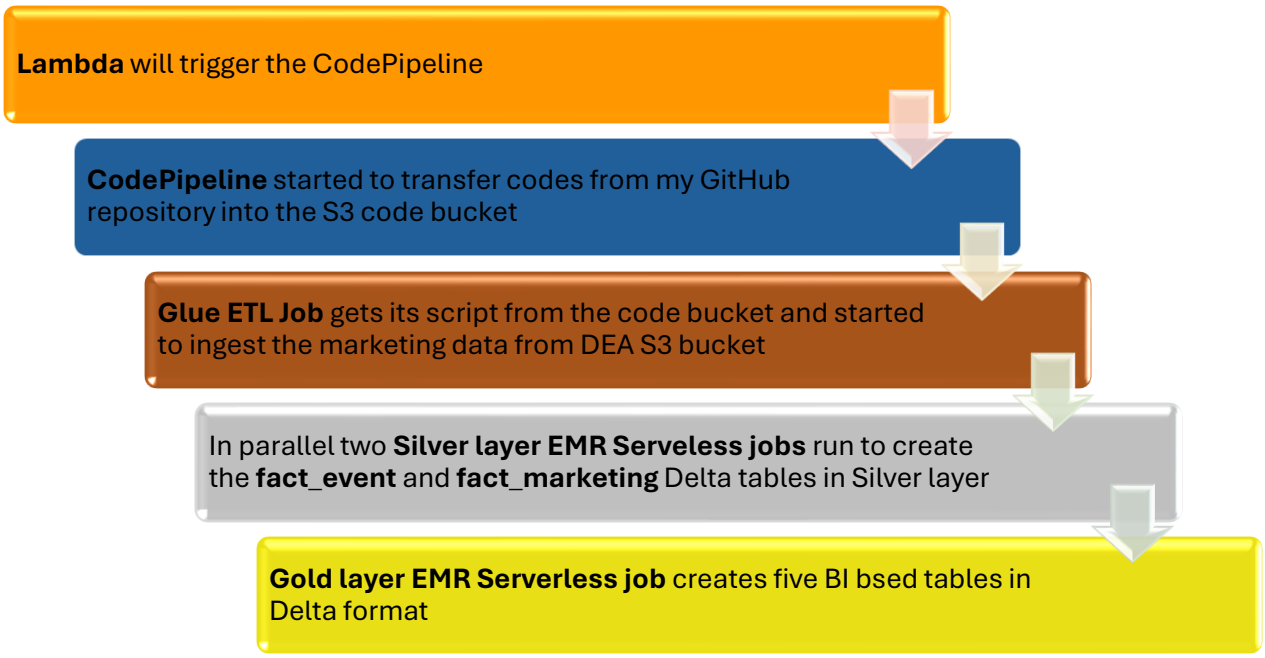
Step 5 – Handling Late-Arriving Data

Late-arriving data is a common challenge in data pipelines, especially when dealing with real-time event streams. To handle this effectively, we distinguish between **event time** and **ingestion time**. Event time refers to the actual timestamp when an event occurs, while ingestion time is when the data is processed and ingested into the pipeline. By maintaining this separation, we can identify and handle records that arrive after the intended time window. To address late data, we implement a **reprocessing window** strategy, typically covering the **last N days**, which allows us to reprocess data for recent periods without affecting the integrity of earlier datasets. The key technique used for efficiently updating late-arriving data is the **Delta Lake MERGE (UPSERT)** operation. This operation allows us to update existing records or insert new records into the dataset based on matching conditions, such as `invitee_id` and `event_start_time`. By using MERGE, we can update historical partitions with new information without needing to perform **full reloads** of the data. This approach prevents unnecessary computation and ensures that only the relevant data is updated, preserving both performance and data consistency.

Step 6 – Visualization (Streamlit)

In the final step, Streamlit dashboards will query data directly from the Gold S3 bucket. I have created a **key button (Run ETL Pipeline)** inside the dashboard for manual triggering the project. I used Pandas for data handling (sufficient for moderate-sized parquet files), and built interactive dashboards for stakeholders with filters, charts, and KPI cards.

As soon as we click on ▶ **Run ETL Pipeline** button in the Streamlit dashboard (maually), or any small change in the GitHub repository, the CodePipeline automatically gets the update from GitHub repo and shares it inside the S3 code bucket. Then, Python and PySpark scripts are available for Glue ETL jobs immedietely. Also, as soon as we click on ▶ **Trigger Glue Job** button in the Streamlit dashboard (manually), the Step Functions is triggered, then all the steps run sequencially:



Conclusion

In this project, a fully automated and scalable data pipeline was designed and implemented to process Calendly webhook events in real time. Leveraging AWS Glue for ETL operations and EMR for distributed data processing, the pipeline efficiently transformed raw event data from the Bronze layer into clean and structured Silver-layer Delta tables, ultimately curating high-quality Gold-layer datasets ready for analytics and business insights.

The orchestration of jobs using AWS Step Functions ensured a robust, dependency-based execution flow, while CI/CD integration with Lambda and API Gateway enabled real-time ingestion of events, reducing manual intervention and improving operational efficiency. Logging and monitoring mechanisms further enhanced transparency and maintainability, allowing for seamless tracking of data transformations and job execution status.

This project demonstrates the effectiveness of a well-architected, cloud-based data pipeline in ensuring data reliability, consistency, and readiness for downstream analytics. By implementing a modular, multi-layered structure, the pipeline not only supports current data processing needs but also provides a foundation for future scalability. Potential enhancements include expanding to additional data sources,

incorporating advanced monitoring and alerting systems, and optimizing performance for higher event volumes, ensuring long-term resilience and adaptability of the data infrastructure.

Overall, the successful deployment of this pipeline highlights the importance of combining automation, cloud services, and best practices in data engineering to deliver a robust solution that can support real-time decision-making and actionable insights.