Coding Assessment

Building a Simple Data Pipeline with Apache Airflow

Introduction

Apache Airflow is a workflow orchestration tool designed to automate, schedule, and monitor complex data processes. Instead of manually running scripts, Airflow lets you organize them into workflows called **DAGs** (**Directed Acyclic Graphs**). It is widely used in data engineering for ETL pipelines, analytics, and machine learning tasks.

Core Features of Airflow

1. DAG-based workflows

 Workflows are represented as DAGs, where tasks are connected in a clear order without loops.

2. Powerful Scheduling

- You can schedule jobs using CRON expressions, intervals, or manual triggers.
- Missed jobs can be backfilled easily.

3. Extensible Operators

- Airflow provides operators like PythonOperator, BashOperator, and SQL operators to cover most data tasks.
- You can also write custom operators.

4. Scalability

Supports distributed execution with Celery, Kubernetes, or Local executors.

5. User Interface

A clean web UI to track DAGs, view logs, retry tasks, and monitor system health.

6. Integration Support

• Works with databases, cloud platforms, data lakes, APIs, and more.

Steps to Build a Pipeline

Step 1: Environment Setup

We'll use Docker Compose to launch Airflow locally.

Get the official docker-compose file

https://airflow.apache.org/docs/apache-airflow/stable/docker-compose.vaml

Create required directories

mkdir -p ./dags ./logs ./plugins

Set user environment variable

```
echo -e "AIRFLOW UID=$(id -u)" > .env
```

Initialize database

docker compose up airflow-init

Start all services

docker compose up

Open the UI at http://localhost:8080 and log in:

Username: airflowPassword: airflow

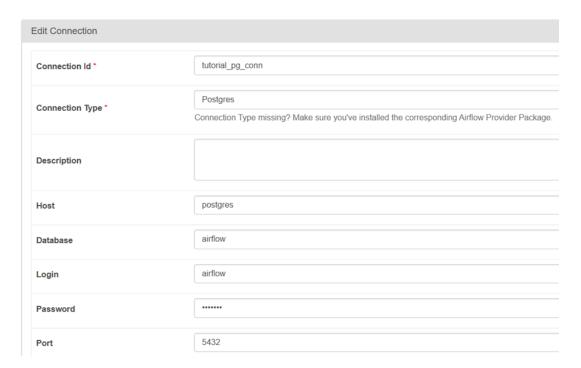
Step 2: Create a Postgres Connection

In the UI, navigate to Admin → Connections and add:

• Conn ID: tutorial pg conn

Type: Postgres
Host: postgres
Database: airflow
Login: airflow
Password: airflow

Port: 5432



Step 3: Define Tables

We'll create two tables:

- employees_raw → temporary staging table
- employees_clean → final processed table

These will be created using the SQLExecuteQueryOperator.

Step 4: Download and Load Data

Use Python tasks to download a CSV file and insert it into the staging table. Airflow hooks handle the database interaction.

Step 5: Merge and Clean Data

A second task will merge deduplicated data into the final table using INSERT ... ON CONFLICT.

Example DAG

```
import datetime
import pendulum
import os
import requests

from airflow.decorators import dag, task
from airflow.providers.postgres.hooks.postgres import PostgresHook
from airflow.providers.postgres.operators.postgres import PostgresOperator

@dag(
    dag_id="process_employees",
```

```
schedule="0 0 * * *",
   start_date=pendulum.datetime(2021, 1, 1, tz="UTC"),
   catchup=False,
   dagrun_timeout=datetime.timedelta(minutes=60),
def ProcessEmployees():
   # Create employees table
   create_employees_table = PostgresOperator(
       task id="create employees table",
       postgres conn id="tutorial pg conn",
       sq1="""
           CREATE TABLE IF NOT EXISTS employees (
                "Serial Number" NUMERIC PRIMARY KEY,
                "Company Name" TEXT,
                "Employee Markme" TEXT,
                "Description" TEXT,
                "Leave" INTEGER
   create_employees_temp_table = PostgresOperator(
       task_id="create_employees_temp_table",
```

```
postgres conn id="tutorial pg conn",
        sql="""
            DROP TABLE IF EXISTS employees temp;
           CREATE TABLE employees temp (
                "Serial Number" NUMERIC PRIMARY KEY,
                "Company Name" TEXT,
                "Employee Markme" TEXT,
                "Description" TEXT,
                "Leave" INTEGER
   @task
   def get_data():
       data_path = "/opt/airflow/dags/files/employees.csv"
       os.makedirs(os.path.dirname(data_path), exist_ok=True)
"https://raw.githubusercontent.com/apache/airflow/main/airflow-core/docs/t
utorial/pipeline_example.csv"
        response = requests.get(url)
       with open(data path, "w") as file:
```

```
file.write(response.text)
       postgres hook = PostgresHook(postgres conn id="tutorial pg conn")
       conn = postgres_hook.get_conn()
       cur = conn.cursor()
       with open(data_path, "r") as file:
            cur.copy_expert(
                "COPY employees_temp FROM STDIN WITH CSV HEADER DELIMITER
AS ',' QUOTE '\"'",
                file,
       conn.commit()
   @task
   def merge_data():
       query = """
            INSERT INTO employees
           SELECT *
           FROM (
               SELECT DISTINCT *
               FROM employees_temp
            ON CONFLICT ("Serial Number") DO UPDATE
            SET
```

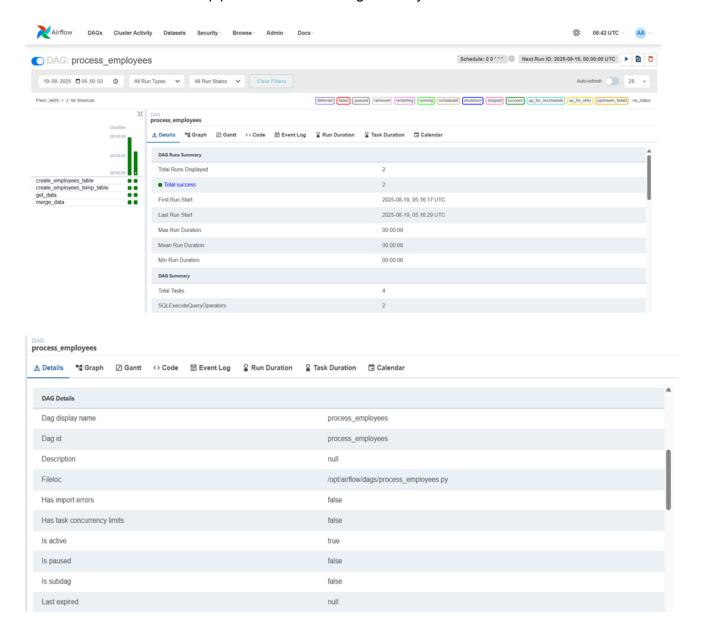
```
"Employee Markme" = excluded."Employee Markme",
              "Description" = excluded. "Description",
              "Leave" = excluded."Leave";
        try:
            postgres hook =
PostgresHook(postgres_conn_id="tutorial_pg_conn")
            conn = postgres_hook.get_conn()
            cur = conn.cursor()
            cur.execute(query)
            conn.commit()
            return 0
       except Exception as e:
           return 1
    # Task dependencies
    [create_employees_table, create_employees_temp_table] >> get_data() >>
merge_data()
dag = ProcessEmployees()
```

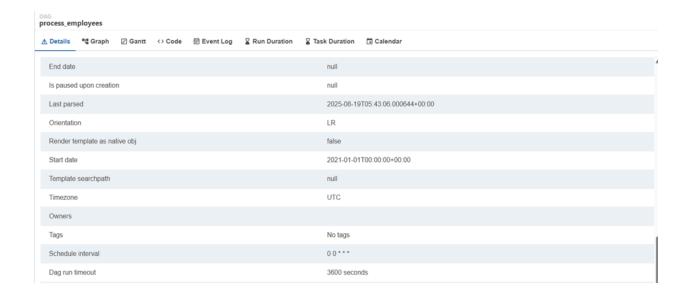
Running the DAG

Once the DAG was saved, it appeared in the Airflow UI. The DAG was triggered manually, and the pipeline successfully:

- Downloaded the CSV file
- Inserted the data into the staging table
- Merged and cleaned the data into the final table

This confirmed that the data pipeline was functioning correctly end-to-end.





Exploring Airflow Views

- **Graph View** → Displays task dependencies in a node graph format.
- **Gantt View** → Timeline view of task duration and overlaps.
- **Tree View** → Quick overview of success/failure across historical runs.

