# Sora Union Data Engineering Task

## Data Warehousing & ETL Process

The project provided us with two CSV files in a Google Sheet, in which we are expected to design a data warehouse and create an ETL process.

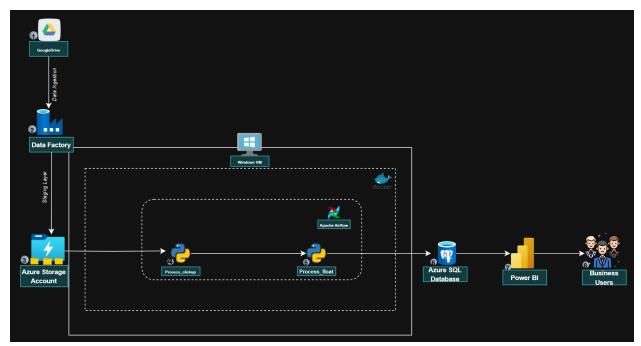
## Assumption

Assuming the data comes in a batch process daily to Google Drive and are ingested to a storage account like **S3** bucket, Google Cloud Storage, or Azure Storage Account (ADLS) using ETL tools like Fivetran, AWS Glue, Azure Data Factory or Dataproc. For this project, we will be using the Azure Storage Account, data Lake Gen 2 for storing the Float and Clickup which will be ingested using the Azure Data Factory.

Since the data gets ingested to the storage account daily, we will be using the concept of getting the latest file (Last Modified Date) in the storage account, performing the necessary transformation and modeling before inserting it into the Azure PostgreSQL Database.

## **Project Architecture**

Based on our early assumption you will notice that data from the Google Drive are ingested to Azure Storage Account (adls) using the Azure Data Factory, we then created a **DAG** process in **Apache Airflow** for Orchestrating the whole process from ingestion of data to transformation and finally loading into Azure PostgreSQL Database (Flexible Server). This process was set to run at **7:00 WAT/GMT+ 1/UTC+1** daily



Project Architecture

## Data Modeling and Warehouse Design

For this reason, we are going to break it into two parts:

- Table Creating with Relationship
- Entity Relationship Diagram

### **Table Creation**

Following the Start Schema design approach we are going to break the data into two fact tables and five-dimension tables.

### **Fact Tables**

This contains the incremental tables that will continue to grow on a steady basis. Optimized for analytical queries.

- fact\_time\_tracking: Stores actual time entries from ClickUp
- fact\_allocation: Stores resource allocation/planning data from Float

### **Dimension Tables**

This is information about the fact table containing necessary information used in the modeling process.

• dim client: Client information

• dim\_project: Project details with client relationships

• dim\_employee: Employee information

• dim\_role: Role definitions

• dim\_date: Date dimension for time-based analysis

### **Data Integrity**

For Data Integrity we ensured following the best practice by creating references and using the indexing approach for query optimization.

### a) Referential Integrity:

- Foreign key constraints on all dimension references
- Ensures data consistency across the warehouse

### b) Indexing Strategy:

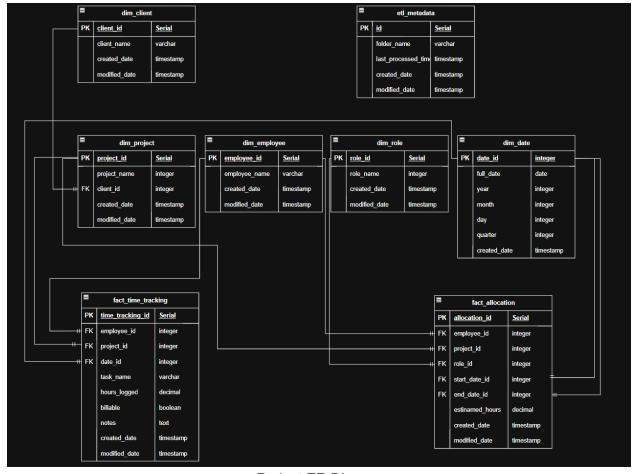
- Primary keys on all tables
- Foreign key indexes for joining optimization
- Composite index on allocation dates
- Created\_date and modified\_date tracking

#### c) ETL Metadata

These are standard data used in keeping records and changes.

## **Entity Relationship Diagram**

Entity-relationship (ER) modeling is a visual approach to data modeling used to represent the structure of a database. It is used to identify the "things" (entities) in a system and how they relate to each other.



Project ER Diagram

### One-to-Many Relationships:

- A client can have multiple projects (1:M)
- A project can have multiple time tracking entries (1:M)
- A project can have multiple allocations (1:M)
- An employee can have multiple time tracking entries (1:M)
- An employee can have multiple allocations (1:M)
- A role can be used in multiple allocations (1:M)
- A date can be referenced by multiple time tracking entries (1:M)
- A date can be the start or end date for multiple allocations (1:M)

### Fact Table Relationships:

### fact\_time\_tracking connects to:

- dim\_employee
- dim\_project
- dim\_date

### fact\_allocation connects to:

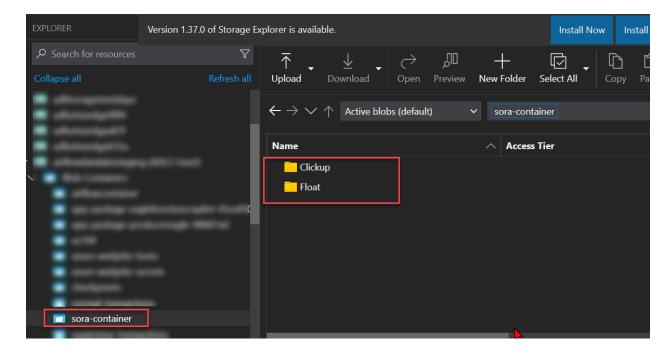
- dim\_employee
- dim\_project
- dim\_role
- dim\_date (twice, for start and end dates)

### **Independent Tables:**

• etl\_metadata is independent and used for ETL process tracking

## ETL Process and Pipeline Development

This section focuses on the ETL process and pipeline development. Firstly let start by creating two empty folders in our *container(prefix- adls)*. These are the containers where the ingestion process will start from.



## Data Ingestion with Data Factory

At this point we are going to create a pipeline using Azure Data Factory that will ingest the data from Google Drive and store it in our staging layer which is the adls.



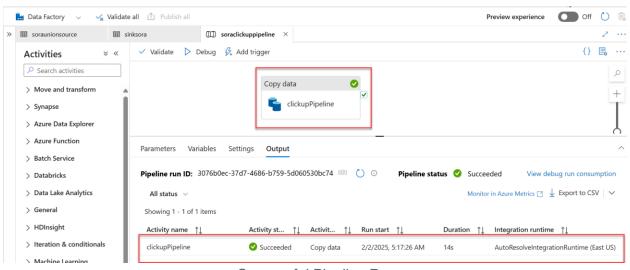
Ingestion Phase

## **Pipeline Creation**

In the Azure Data Factory the following components are created to achieve this.

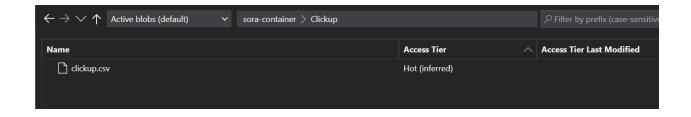
- Source Dataset
- Source Linked Service
- Activity (Copy Activity Google Drive to adls)
- Sink Linked Service
- Sink Dataset

From the image below you will notice the data copied successfully from Google Drive to ADLS which serves as our storage layer.



Successful Pipeline Run

We can confirm the data in the storage account.



### Transformation and Loading Preparation

At this stage we will be developing the transformation logic and creating and orchestration process using Apache Airflow

### Pre-requisite

- Docker Desktop (Using Windows)
- Virtual Machine/ EC2 Instant (Windows Server)
- WSL Windows Subsystem for Linux (Applicable for only Windows Users)
- Preferred IDE VSCode

## Setting Airflow on Docker

By going through the official documentation on Airflow Docker was a straight process. <a href="https://airflow.apache.org/docs/apache-airflow/stable/howto/docker-compose/index.html#running-airflow-in-docker">https://airflow.apache.org/docs/apache-airflow/stable/howto/docker-compose/index.html#running-airflow-in-docker</a>

### Folder Breakdown

#### Sora Union/

- >> config
- -- .env
- -- config.py
- >> dags
- -- etl\_dag.py
- -- etl\_process.py
- -- utils.py
- >> logs
- >> plugins
  - .env: Environment variables and sensitive configuration. Stores sensitive configuration like:

Azure Storage credentials, PostgreSQL database connection details.

- **config.py:** Configuration loader and settings management. Loads environment variables and defines constants used across the application.
- etl\_dag.py: Airflow DAG definition and task orchestration.
  - process\_clickup: Processes ClickUp time tracking data
  - process\_float: Processes Float resource allocation data
  - Configures scheduling (runs daily at 6 AM UTC)
- etl\_process.py: Core ETL transformation logic. Contains the ETLProcess class which handles:
  - Dimension table management (clients, projects, employees, roles)
  - Data transformation logic for both ClickUp and Float data
  - Fact table loading for time tracking and resource allocation
  - Incremental loading through metadata tracking
- utils.py: Utility classes for Azure and PostgreSQL connections.

#### Provides utility classes:

- AzureStorageClient:
- o Handles connections to Azure Data Lake Storage
- Manages file listing and reading
- PostgresClient:
- Manages database connections
- Provides methods for querying and data loading

### Airflow Orchestration

After successfully setting up your code you can run it on the Airflow Webserver UI and see it works as expected.

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                                                                                                                                                                                                                                                                                          ▷ ~ □ …
            EXPLORER
                                                                                                                   etl_process.py
etl_dag.py X
init_.py config
                                                                    54 def run_float_etl(**context):

10 logger.error(t rioat bit process talled: {str(e)})
            > pycache
                                                    80
81 # Create the DAG
82 with DAG(
83 'sona_etl_pi;
default_angs
                                                                                      'sora_etl_pipeline',

default_args=default_args,

description='ETL pipeline for ClickUp and Float data',

schedule_interval='0 6 * * * * ', # 7 AM WAT (6 AM UTC)

start_date=days_ago(1),

catchupeFalse,
                                                                        89 tags=
90 ) as dag:
                                                                                          tags=['etl', 'sora'],

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              config.py
                                                                       airflow-scheduler-1 exited with code 0
                                                                        airflow-webserver-1 exited with code 0
               docker-compose.yaml
             ■ Float allocations.csv
                                                                                                             1:signal-handler (1738401633) Received SIGTERM scheduling shutdown...
                                                                                                           l:signal-handler (1734401633) Received SIGTEM scheduling shutdown...
2025-02-01 09:20:33.486 UTC [1] LOG: received fast shutdown request
2025-02-01 09:20:33.599 UTC [1] LOG: aborting any active transactions
1:M 01 Feb 2025 09:20:33.512 * User requested shutdown...
1:M 01 Feb 2025 09:20:33.512 * Saving the final RDB snapshot before exiting.
1:M 01 Feb 2025 09:20:33.533 * DB saved on disk
1:M 01 Feb 2025 09:20:33.534 # Redis is now ready to exit, bye bye...
2025-02-01 09:20:33.576 UTC [1] LOG: background worker "logical replication launcher" (PID 31) exite

■ Modeling Reason.txt

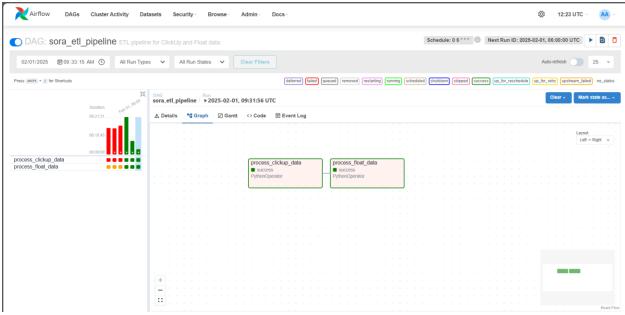
              ■ Modeling Table.txt
              ■ Note.txt

≡ requirements.txt

                                                                         d with exit code 1
                                                                                                            | 2025-02-01 09:20:33.603 UTC [26] LOG: shutting down
| 2025-02-01 09:20:33.813 UTC [1] LOG: database system is shut down
                                                                         redis-1 exited with code 0
postgres-1 exited with code
                                                                        (sora_env) PS C:\Users\Temidayo\Desktop\Sora Union> ^Ctch
          ® 0 ▲ 0 🐕 0 🕏 Live Shar
```

### docker-compose up

### Process\_clickup\_data >> process\_float\_data



Airflow Orchestration

## Test and Validate ETL Process

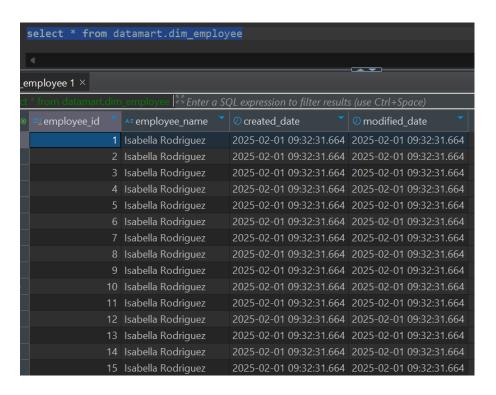
After successfully running the entire ETL process we can test it by using the SELECT statement in PostgreSQL Database.

select \* from datamart.dim\_client

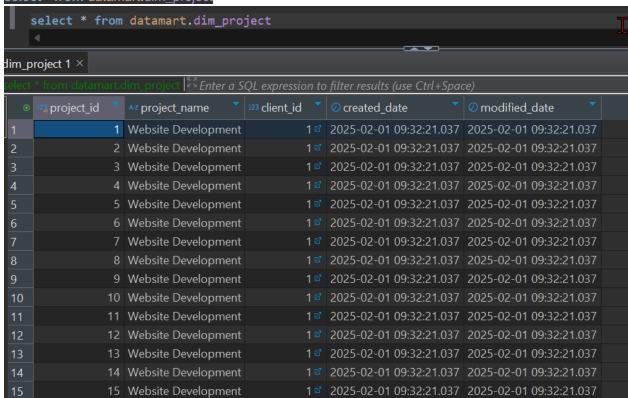
#### select \* from datamart.dim client limit 100 dim client 1 imes🖺 Enter a SQL expression to filter results (use Ctrl+Space client\_id A-z client\_name ② created\_date modified\_date 2025-02-01 09:32:15.417 2025-02-01 09:32:15.417 1 Client 1 2 2 Client 1 2025-02-01 09:32:15.417 2025-02-01 09:32:15.417 2025-02-01 09:32:15.417 2025-02-01 09:32:15.417 3 Client 1 4 Client 1 2025-02-01 09:32:15.417 2025-02-01 09:32:15.417 4 5 Client 1 2025-02-01 09:32:15.417 2025-02-01 09:32:15.417 2025-02-01 09:32:15.417 2025-02-01 09:32:15.417 6 Client 1 6 7 Client 1 2025-02-01 09:32:15.417 2025-02-01 09:32:15.417 2025-02-01 09:32:15.417 2025-02-01 09:32:15.417 8 Client 1

#### select \* from datamart.dim date select \* from datamart.dim\_date \_date 1 × 3 2025-02-01 09:32:11.223 20,230,703 2023-07-03 2023-07-04 3 2025-02-01 09:32:11.223 2023-07-05 3 2025-02-01 09:32:11.223 2023-07-06 3 2025-02-01 09:32:11.223 2023-07-07 3 2025-02-01 09:32:11.223 2023-07-08 3 2025-02-01 09:32:11.223 2023-07-09 3 2025-02-01 09:32:11.223 2023-07-10 3 2025-02-01 09:32:11.223 2023-07-11 3 2025-02-01 09:32:11.223 2023-07-12 3 2025-02-01 09:32:11.223 2023-07-13 3 2025-02-01 09:32:11.223 3 2025-02-01 09:32:11.223 2023-07-15 3 2025-02-01 09:32:11.223 20,230,716 2023-07-16 3 2025-02-01 09:32:11.223

select \* from datamart.dim\_employee

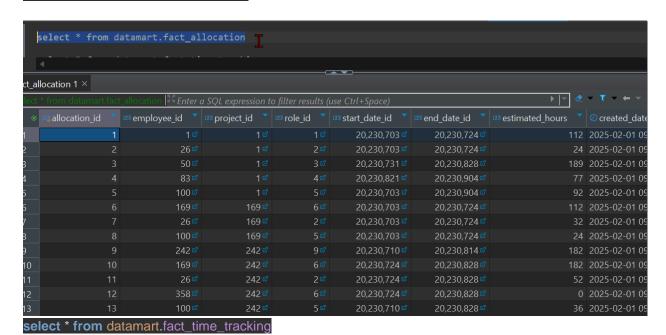


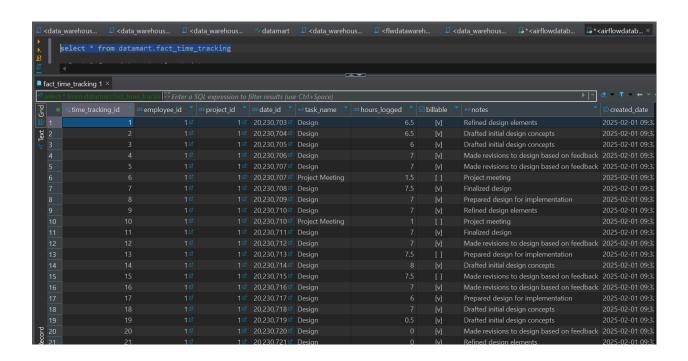
select \* from datamart.dim project



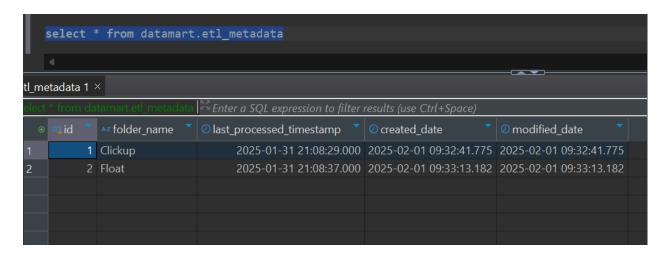
select * from datamart.dim_role					
ш.	loot * from determine fort ellocation				
dim_role 1 ×					
select * from datamart.dim role Expression to filter results (use Ctrl+Space)					
•	123 role_id		^z role_name	⊘ created_date ▼	
1		1	Product Designer	2025-02-01 09:33:06.922	2025-02-01 09:33:06.922
2		2	Design Manager	2025-02-01 09:33:06.922	2025-02-01 09:33:06.922
3		3	Front End Engineer	2025-02-01 09:33:06.922	2025-02-01 09:33:06.922
4		4	QA Engineer	2025-02-01 09:33:06.922	2025-02-01 09:33:06.922
5		5	Project Manager	2025-02-01 09:33:06.922	2025-02-01 09:33:06.922
6		6	Brand Designer	2025-02-01 09:33:06.922	2025-02-01 09:33:06.922
7		7	Design Manager	2025-02-01 09:33:06.922	2025-02-01 09:33:06.922
8		8	Project Manager	2025-02-01 09:33:06.922	2025-02-01 09:33:06.922
9		9	Localization Specialist UK	2025-02-01 09:33:06.923	2025-02-01 09:33:06.923
10		10	Brand Designer	2025-02-01 09:33:06.923	2025-02-01 09:33:06.923
11	1	11	Design Manager	2025-02-01 09:33:06.923	2025-02-01 09:33:06.923
12	1	12	Brand Designer	2025-02-01 09:33:06.923	2025-02-01 09:33:06.923
13	1	13	Project Manager	2025-02-01 09:33:06.923	2025-02-01 09:33:06.923

select \* from datamart.fact\_allocation





select \* from datamart.etl\_metadata



## Conclusion

To get a high level of accuracy the following process where followed, having designed the model, had a high level of data quality change and improved the query by optimizing using index on certain columns.