

Build Robust Automated Data Modeling

A Beginner's Guide to Collaborative Data Modeling with DBT and Airflow

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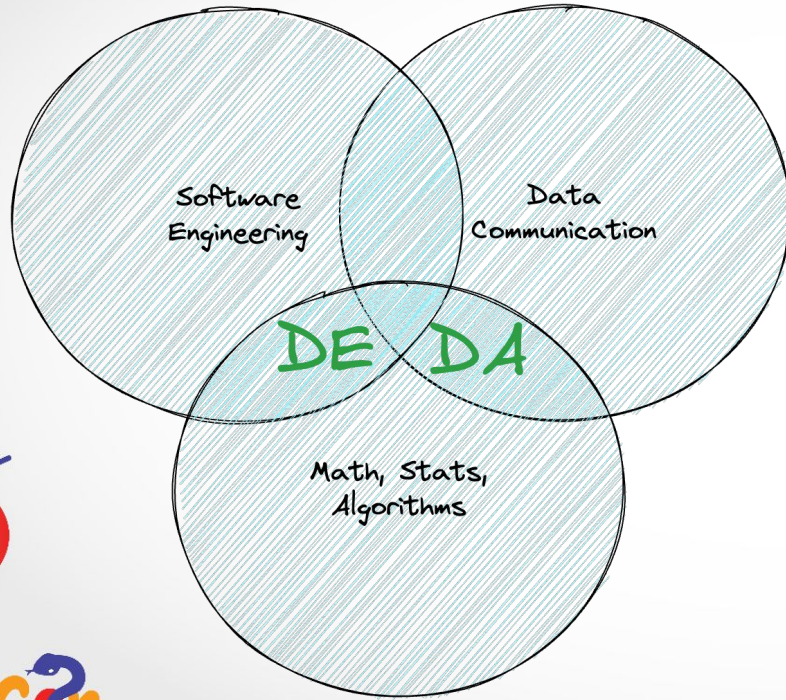
Founder & Mod @Pelajar Data



https://linktr.ee/as_sulthoni



Analyst and Engineer Role



Data Analysts are strong in :

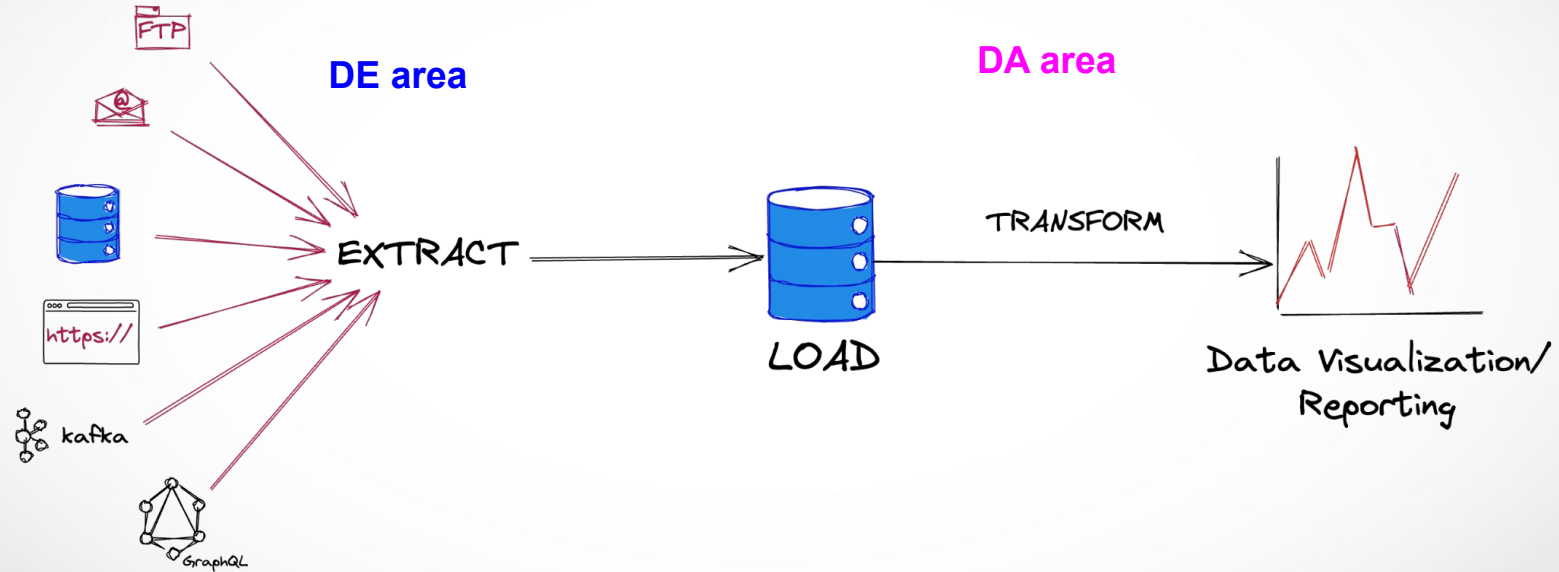
- Business Subject
- Data Visualization and Presentation
- Logic/formula on creating metrics and KPI

Data Engineers are strong in :

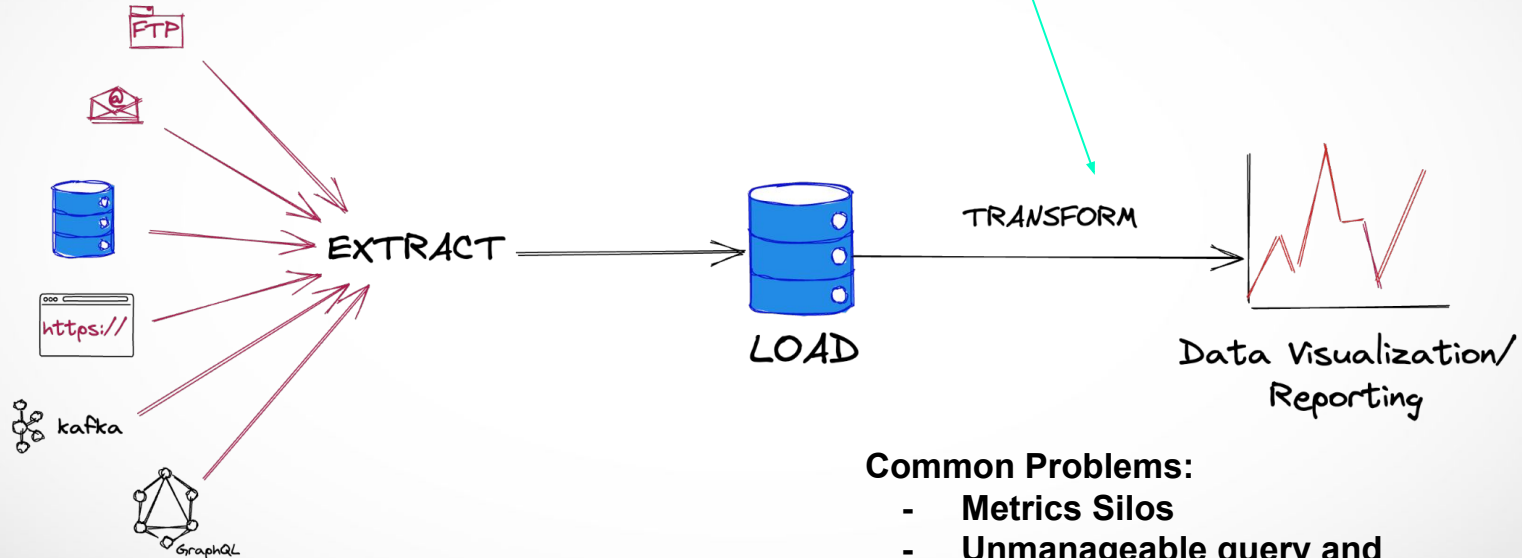
- Software Engineer best practices
- Automation
- Computation optimization

ELT (Extract, Load, Transform) Design

Before



Before

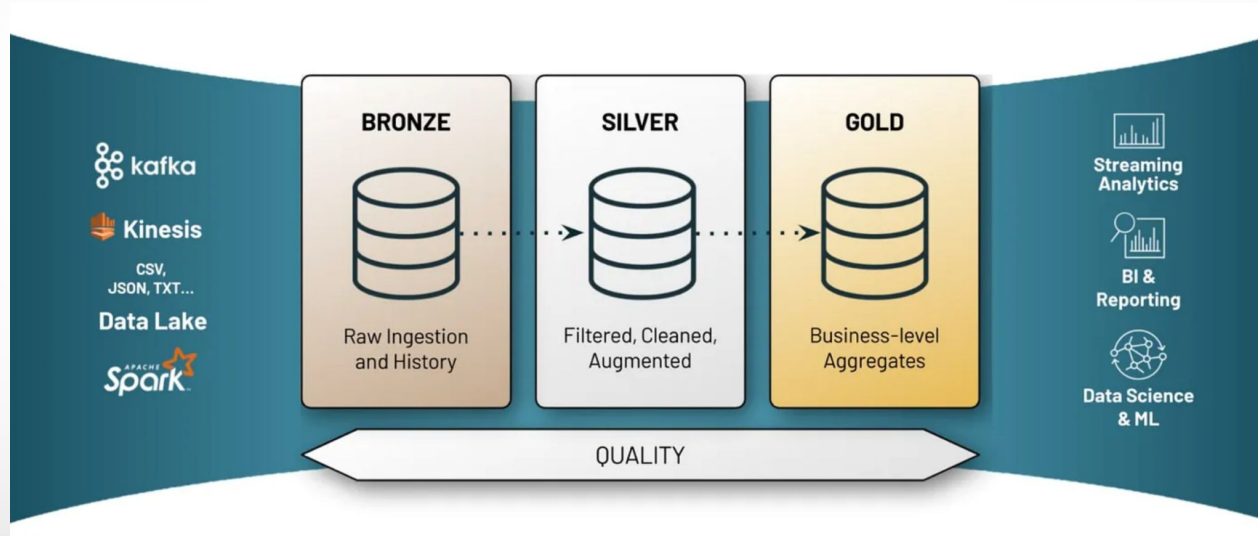


Common Problems:

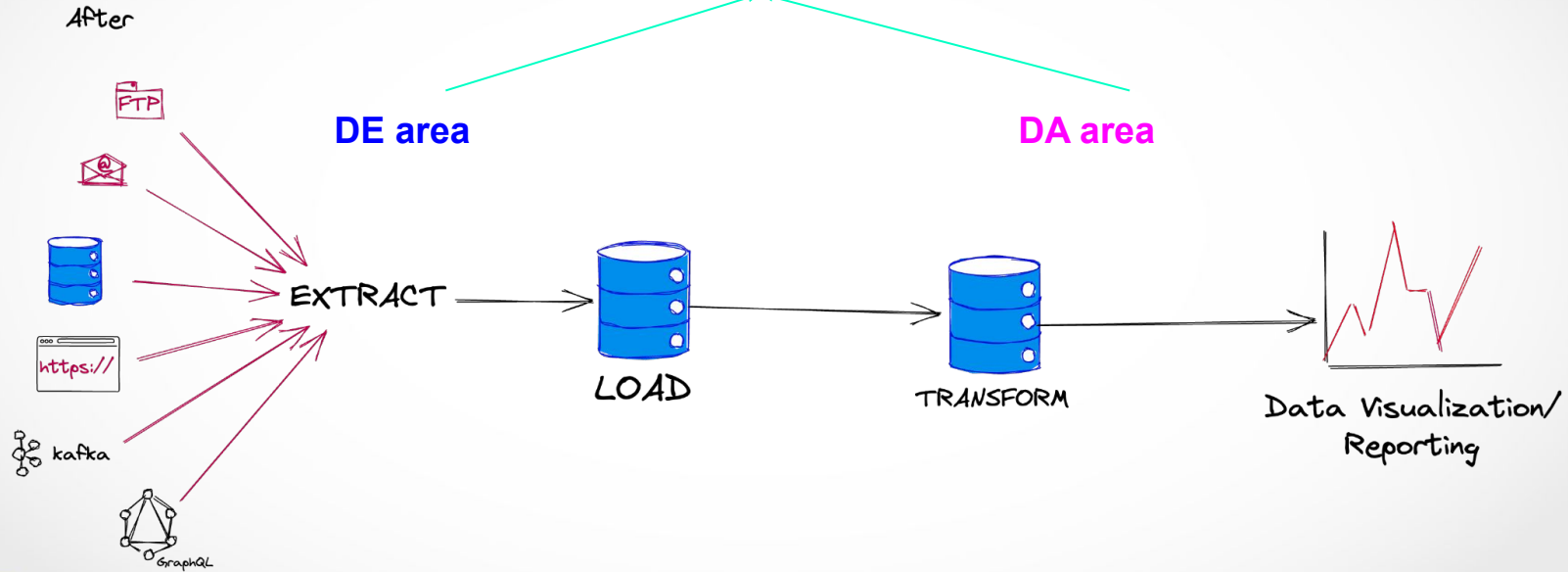
- Metrics Silos
- Unmanageable query and dashboard
- Data Quality is poor

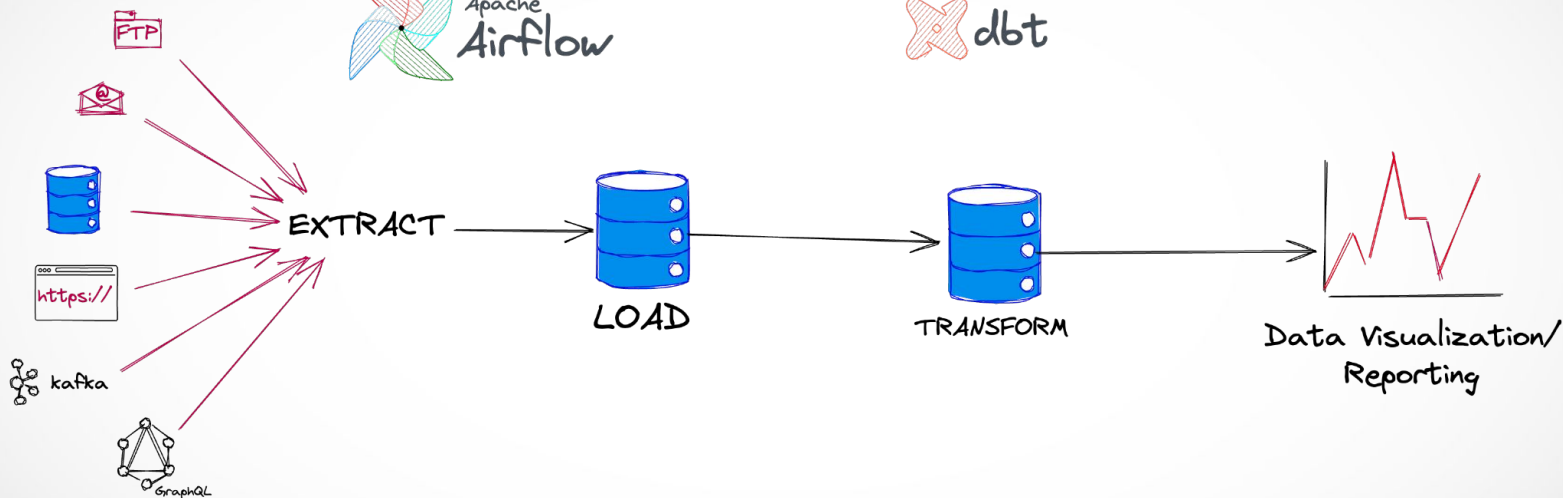
Data Modeling

Data Transformation within our database / data warehouse in order to organize and structure data.



- Centralized logic
- QA on Data
- Code Review







Airflow

Apache Airflow™ is an open-source platform for:

- **Developing**
- **Scheduling**
- **monitoring batch-oriented** workflows.



DBT

dbt is a **data transformation** workflow that helps you get more work done while producing higher quality results.

- Modularity
- Test and QA
- Eliminate Silos

Repo Structure

<https://github.com/assulthoni/airflow-dbt-integration>

```
.
├── Dockerfile
├── LICENSE
├── README.md
├── config
├── dags
│   ├── dbt
│   │   └── simple_data_modeling
│   │       ├── README.md
│   │       ├── analyses
│   │       ├── dbt_packages
│   │       ├── dbt_project.yml
│   │       ├── macros
│   │       ├── models
│   │       │   ├── continent_metrics_model.sql
│   │       │   ├── example
│   │       │   ├── gov_continent_metrics_model.sql
│   │       │   ├── gov_metrics.sql
│   │       │   ├── schema.yml
│   │       │   └── source.yml
│   │       ├── profiles.yml
│   │       ├── seeds
│   │       ├── snapshots
│   │       └── tests
│   ├── dbt_dag_advance.py
│   └── dbt_dag_basic.py
├── db-init-scripts
│   └── world.sql
├── docker-compose.yaml
├── plugins
└── requirements.txt
```

DBT Model Example

```
{{ config(materialized='table') }}

WITH country_data AS (
    SELECT
        governmentform,
        continent,
        code,
        surfacearea,
        population
    FROM {{ source('public', 'country') }}
),

final AS (
    SELECT
        governmentform,
        continent,
        COUNT(code) AS country_count,
        SUM(surfacearea) AS total_area,
        SUM(population) AS total_population
    FROM country_data
    GROUP BY governmentform, continent
)

SELECT *
FROM final
```

```
{{ config(materialized='table') }}

WITH country_data AS (
    SELECT
        governmentform,
        continent,
        country_count,
        total_area,
        total_population
    FROM {{ ref('gov_continent_metrics_model') }}
),

final AS (
    SELECT
        governmentform,
        COUNT(DISTINCT continent) AS ctd_continent,
        SUM(total_population) AS total_population
    FROM country_data
    GROUP BY governmentform
)

SELECT *
FROM final
```


Orchestrate DBT

```
import os
from datetime import datetime
from airflow import DAG
from airflow.operators.bash_operator import BashOperator

CURRENT_DIR = os.getcwd()
DBT_DIR = CURRENT_DIR + '/dags/dbt/simple_data_modeling'

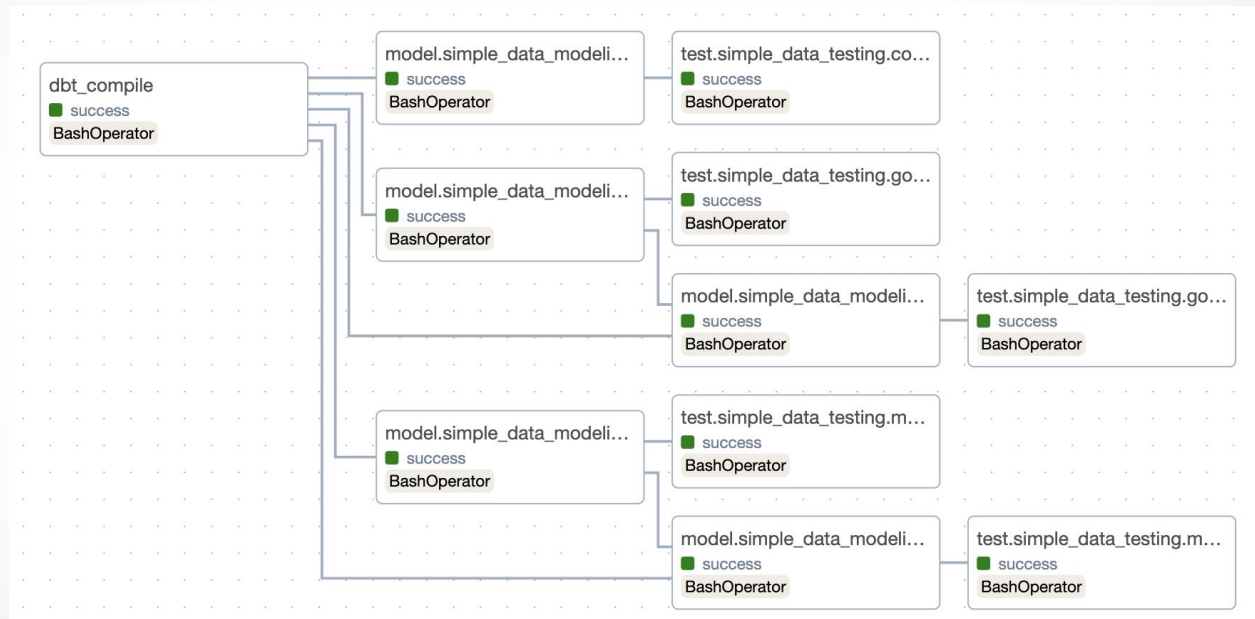
dag = DAG(
    "dbt_dag_basic",
    start_date=datetime(2020, 12, 23),
    description="A sample Airflow DAG to invoke dbt runs using a BashOperator",
    schedule_interval='@daily',
    catchup=False,
)

task_run = BashOperator(
    dag=dag,
    task_id="dbt_run",
    bash_command=f"cd {DBT_DIR} && dbt run --profiles-dir ."
)

task_test = BashOperator(
    dag=dag,
    task_id="dbt_test",
    bash_command=f"cd {DBT_DIR} && dbt run --profiles-dir ."
)

task_run >> task_test
```

DAG Graph on DBT



Orchestrate DBT (Advance)

```
import os
import json
from datetime import datetime
from airflow import DAG
from airflow.operators.bash_operator import BashOperator

CURRENT_DIR = os.getcwd()
DBT_DIR = CURRENT_DIR + '/dags/dbt/simple_data_modeling'

dag = DAG(
    "dbt_dag_advance",
    start_date=datetime(2020, 12, 23),
    description="A sample Airflow DAG to invoke dbt runs using a BashOperator",
    schedule_interval="@daily",
    catchup=False,
)

def load_manifest():
    local_filepath = f"{DBT_DIR}/target/manifest.json"
    with open(local_filepath) as f:
        data = json.load(f)
    return data
```

Orchestrate DBT (Advance)

```
def make_dbt_task(node, dbt_verb):  
    model = node.split(".")[1]  
    if dbt_verb == "run":  
        dbt_task = BashOperator(  
            dag=dag,  
            task_id=node,  
            bash_command=(  
                f"cd {DBT_DIR} && "  
                f"dbt {dbt_verb} --models {model} "  
                f"--profiles-dir ."  
            ),  
        )  
    elif dbt_verb == "test":  
        node_test = node.replace("model", "test")  
        dbt_task = BashOperator(  
            dag=dag,  
            task_id=node_test,  
            bash_command=(  
                f"cd {DBT_DIR} && "  
                f"dbt {dbt_verb} --models {model} "  
                f"--profiles-dir ."  
            ),  
        )  
    return dbt_task
```

Orchestrate DBT (Advance)

```
dbt_compile = BashOperator(
    dag=dag,
    task_id='dbt_compile',
    bash_command=(
        f"cd {DBT_DIR} && "
        f"dbt compile "
        f"--profiles-dir ."
    ),
)

data = load_manifest()
dbt_tasks = {}

for node in data["nodes"].keys():
    if node.split(".")[0] == "model":
        node_test = node.replace("model", "test")
        dbt_tasks[node] = make_dbt_task(node, "run")
        dbt_tasks[node_test] = make_dbt_task(node, "test")

for node in data["nodes"].keys():
    if node.split(".")[0] == "model":
        node_test = node.replace("model", "test")
        dbt_compile >> dbt_tasks[node] >> dbt_tasks[node_test]
        for upstream_node in data["nodes"][node]["depends_on"]["nodes"]:
            upstream_node_type = upstream_node.split(".")[0]
            if upstream_node_type == "model":
                dbt_compile >> dbt_tasks[upstream_node] >> dbt_tasks[node]
```


Run Example

airflow-dbt-integration	-	Running (7/8)			
redis-1 21ad6a91fc6a	redis:latest	Running	10 minutes ag		
postgres-1 539bff642b02	postgres:13	Running	10 minutes ag		
airflow-init-1 43e827c4680f	airflow-dbt-integration-airflow-init:latest	Exited			
airflow-webserver-1 7298b6da4eae	airflow-dbt-integration-airflow-webserver:latest	Running	8080:8080	10 minutes ag	
airflow-scheduler-1 c92350f4a00a	airflow-dbt-integration-airflow-scheduler:latest	Running		10 minutes ag	
airflow-triggerer-1 44252204ae42	airflow-dbt-integration-airflow-triggerer:latest	Running		10 minutes ag	
airflow-worker-1 abc02d794943	airflow-dbt-integration-airflow-worker:latest	Running		10 minutes ag	
myPostgresDB-1 836f4f762dc5	postgres:13	Running	5432:5432	10 minutes ag	

Reference

- <https://aws.amazon.com/what-is/data-modeling/>
- <https://airflow.apache.org/docs/apache-airflow/stable/howto/docker-compose/index.html>
- <https://docs.astronomer.io/learn/airflow-dbt>
- <https://piethein.medium.com/middleware-architecture-best-practices-for-managing-bronze-silver-and-gold>



QnA

Feel free to ask/give any question or feedback